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Editorial

Praise be to Allah and peace and prayers be upon his messenger.

Dear reader,

We are pleased to present this 3rd volume of Merowe University of Technology – Abdullatif Alhamad journal.We appreciatedyour satisfaction and your feedback to the previous volumes and we are looking forward to receiving yourvaluable comments of the present volume In this volume, we have focused on scientific and knowledge diversity with aview to lending a hand that actively participates in the rebuilding of our beloved country

In this volume you will find diversified topics carefully selected to cover a wide range of science branches and knowledge.

The journal will soon be published online to reach wider readership. Finally, we are full of hope that you will find this volume of value in helping science and knowledge. We invoke Allah to guide us in the right direction

Editorial Board

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Articles Page

Diesel Engine Fault Detection Based on Wavelet Transform Method Using LabView Software

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Abstract:

This paper concerns with condition monitoring method of a four-stroke, 295 a diesel engine. The fault of the internal-combustion engine was detected by using the vibration signals of the cylinder head. Based on the data-acquisition system built with LabVIEW software, the cylinder-head vibration signals were captured through a piezoelectric acceleration sensor while the engine was running at speeds (620 and 1000 rpm) and two loads (0 and 30 N.m). The engine was running under five working conditions such as single cylinder shortage, double cylinders shortage, intake manifold obstruction, exhaust manifold obstruction and normal condition. After decomposing, the vibration signals with db5 wavelet and decomposition level 5, therefore the energy extracted from each frequency sub-band of normal and abnormal conditions as a feature of engine fault diagnosis. Thereby, the fault distinguished by the comparing the accumulations of energy in each sub-band of healthy and faulty conditions. The results showed that, detection of fault by using wavelet analysis is successful and practicable. Finally, we identified fault diagnosis by applied the back-propagation neural network (BPNN) and Support Vector Machine (SVM) on the signal collected from the engine.

Keywords: diesel engine- vibration signal- fault condition- Labview- wavelet, fault

مستخلص

تتناول هذه الورقة طريقة مراقبة الحالة لمحرك ديزل رباعى الأشواط 295 محرك. تم اكتشاف خطأ محرك الاحتراق الداخلى بإستخدام اشارات الإهتزازلرأس الاسطوانة إستناداً الى نظام الحصول على البيانات المصممة بواسطة برنامج Labview. تم التقاط إشارات اهتزاز رأس الأسطوانة من خلال مستشعر تسارع كهرضغطية أثناء تشغيل المحرك بسرعات (620 و1000 دورة فى الدقيقة) وتحميلات (0 30 نانومتر) .كان المحرك يعمل تحت خمسة ظروف عمل نقص الاسطواانة الواحدة. وننقص الأسطوانات المذدوجة . وعرقلة مشعب السحب . وعرقلة مشعب العادم والحالة الطبيعية. بعد التحلل ، تقوم اشارات الاهتزاز بمستوى المويجات db5 ومستوى التحلل 5 . وبالتالى الطاقة المستخرجة من كل نطاق فرعى للتردد فى الظروف الطبيعية وغير الطبيعية كميزة لتشخيص خطأ المحرك وبالتالى فإن الخطأ يتميز بمقارنة تراكمات الطاقة فى كل نطاق فرعى بظروف صحية خاطئة. أظهرت النتائج أن اكتشاف الخطأ باستخدام تحليل المويجات يكون نا جحاً وعملياً. وأخيراً حددنا تشخيص العيوب بتطبيق الشبكة العصبية ذات الإنتشار الخلفى (BPNN) وآلة دعم المتجهات (SVM) على الإشارة التى تم جمعها من المحرك .

Introduction:

For many centuries, the only way of detecting and locating faults was using biological senses. At that time, everything was based on observing, listening, smelling and touching different parts of the system. Later, a greater flow of accurate fault information was enabled by introducing measuring equipment, and nowadays computers made possible a dramatic progress in fault detection and identification. The ever-growing demand for excellent operational efficiency and safety in the design and development of automated guided vehicles leads to the development of diagnostic strategies that could cover the major potential faults of the automated guided vehicles. Fault diagnosis as an engineering discipline has spread into the machine design and development practices of general aerospace and high technology industries of the present [1]. Fault detection is the decision if a fault is present or not while fault diagnosis provides more information about the nature or localization of the failure. This information can be used to minimize downtime and to schedule adequate maintenance action [2]. Advanced engine maintenance programs incorporate various methods for monitoring the health of engine components, helping us to check if the engine is running under its normal conditions and also enable us to foresee any malfunctions or abnormal operations and diagnose if any defect is present [3]. Diesel engine is the power source of many machines. It generates the necessary drive power to overcome the resistance loads by burning fuel and converting the energy content of the inlet mixture to mechanical motions. Initial faults not only degrade the performance of the engine it self but also bring significant economic losses to the user. To reduce the negative influences to a minimum, many monitoring methods have been studying in the last two decades. Parameters such as vibration, temperature, lubricant quality and power consumption can be used to monitor the mechanical status of equipment

[4]. Engine failures could be caused either by combustion related to subsystems, such as the fuel-injection system, the cylinder/piston system, the inlet and outlet valve system, or by non-combustion related to subsystems, including all auxiliary devices such as turbochargers, gears, bearings and electronic control units. Engine misfire, knocking, insufficient power output, poor fuel efficiency, excessive exhaust smoke or noise and vibration, all of them have fault symptoms of a diesel engine. To minimize or to prevent the occurrence of unpredicted engine failures, the operating state and health of a diesel engine need to be monitored continually. So that a fault symptom and its cause could be diagnosed and dealt with at the early stage before it becomes a functional failure [5]. The method for developing analysis process is studied in this paper in order to monitor four-stroke, 2 cylinders and a 295 diesel engine using vibration signal. Vibration signal was acquired through piezoelectric acceleration sensors attached to a surface of the cylinder head of the engine using LABVIEW program. This signal was analyzed by using frequency-domain techniques to determine various parameters. Then the engine states could be predicted. Moreover, vibration signal detected on the diesel engine is composed of various events that associated with some mechanical processes in the engine. All events were combined to create a complicated vibration signal. This signal could be mapped onto various processes associated with a cylinder head such as one cylinder shortage, double cylinders shortage, intake manifold obstruction, exhaust manifold obstruction and normal condition, using wavelet transform method based on Labview software. To achieve the above objectives, there are two sets of tests will be conducted, these tests are:
a. To setup the diesel engine to allow observations of the vibration signal characteristics, when the diesel engine was running at healthy condition.
b. To setup the diesel engine to allow observations of the vibration signal characteristics, when the diesel engine was suffering from abnormal conditions.
Analyze these signals by using the frequency-domain techniques. Then, the results or information extracting from the analyzing of these signals related to engine processes can be used to identify or diagnosis faults by comparing detected deviations between normal and abnormal conditions in the engine [6].

2. Materials and the hardware design of the fault diagnosis system:

2.1. The test diesel engine of experimental study:

The test diesel engine conducted in this experimental was 295 diesel engine. The engine consists of two-cylinders, four strokes, 13.5 Kw power and 1500 rpm. It has excellent technical performance and operating stability. The specification of the 295 diesel engine was shown in table.1.

Table 1: Main design features of the test 295 diesel engine:

Items	Parameters	Items	Parameters
Type	Vertical, four-stroke	Rated speed	r/min 1500
Number of cylinders	cylinders 2	(Dimensions(mm	1514×598×810
Bore × stroke	mm 115×95	Cooling system	Water cooling
Rated Power	kW 13.5	Quality	kg 345
Inlet		Naturally aspirated	

A schematic diagram of a data acquisition (DAQ) system for monitoring the diesel engine and tools of signal collected, based on LabVIEW virtual instrument was shown in figure 1.

Figure 1: The schematic diagram of the diesel engine fault diagnosis system, physi

The engine load has measured by current dynamometer CW40 manufactured by Xiangjiang Power Testing Instrument Co. Ltd. Was used in this experiment to measure and control the engine torque and speed. National Instrument PCI 6040 E-card and LabVIEW software were used for data acquisition. Data acquisition is the card that placed directly inside the computer and used as an interface in order to control the plant in real time environment. Two Piezoelectric acceleration sensors - type CA-YD-106A, the features of the sensors are small size, high sensitivity and low weight. Because the voltage signal from the piezoelectric sensor is very weak, multi-Channel charge amplifier YE5853A used to facilitate later observation, acquisition, signal analysis and processing. The SCB-68 is a shielded connector block with 68 screw terminals for easy connection to National Instruments 68-pin product used in this experiment. A Lenovo computer Pentium 4 with 3.00 GHz processor, 512 MB RAM and 80 GB HD was used.

2.2 Sensors installation on the diesel engine head:

Vibration signals have measured using the most sensitive piezoelectric acceleration sensor placed on the cylinders head bolts. Which they are tightening the cylinder head on the engine body and engine fundamental parts. The position of sensors on the internal combustion diesel engine was in figure 2.

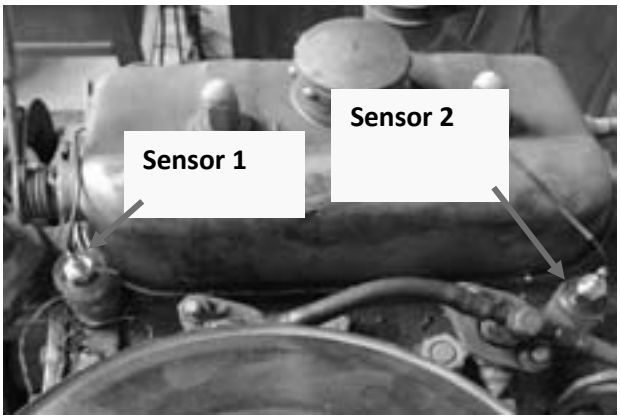


Figure 2: The Position of Sensors on the diesel engine head

2.3 Setup of experiment:

The experiment presentd in this study used the vibration data obtained from the test diesel engine. Data was gathered from five different conditions, single cylinder shortage, double cylinders shortage, intake manifold obstruction, exhaust manifold obstruction and normal condition. Single cylinder and double cylinders misfiring were designed by cutting diesel oil route artificially, while intake and exhaust manifolds obstruction designed by placing a gasket in the opening between air inlet/exhaust outlet manifold pipe and engine body in order to decrease the normal opening of the air inlet and exhaust outlet. The engine speeds in this experiment set as 620 r/min and 1000 r/min, and the load torque was set as 0 N.m (no load) and 30 N.m., in summary, the On-line condition monitoring can be shown in figure 3.

2.4 The selected sampling frequency and sampling points in this study:

In the diesel engine, the frequency of the vibration excitation was changed according to the change of the vibration excitation sources, speed and load. Some trials have shown that, the diesel engine's head vibration frequency was 10 kHz [7]. For each of the above-mentioned five operating conditions, two speeds and two loads were used. Then for each treatment, a signal was collected from the engine's head using of the sensor. And after that, the signal was transferred to the computer through the data-acquisition units. 101 amplitudes were randomly se-

lected for each of the groups above. The rate of the sample that taken in this experiment was 20 kHz or 20 k samples per second as a floating-point data. Duration of each vibration signal was four seconds. 5000 points were captured from each second. This rate of the sample which is too difficult to analyze it all; therefore, only 4096 samples were randomly chosen, in order to facilitate the analysis process.

3. Vibration signal:

Investigators all over the world, focused on setting up and testing systems and techniques for engine fault detection. Those are mainly based on the analysis of: In-cylinder pressure, ionization current or breakdown voltage, a crankshaft angular speed, temperature and oxygen concentration and vibration signals. In this study, vibration signals established as the way of recording required data set because of the ease of measurement and the rich contents of informationVibration measurement is one of the most common fault diagnosis methods. Vibration signal from the machine surface as the multi-stimulation response, not only contains stimulation information in detail, but also contains the transferring characteristics and relative fault information. So it is an effective method to carry out performance of monitoring and fault diagnosis without disassembling the engine [8]. Diagnosis techniques for diesel engine faults using vibration signals may be broadly classified into three categories, namely time-domain analysis, frequency-domain analysis, and time-frequency analysis techniques. All of them have been employed to process the vibration signals used in fault diagnosis of plant machinery [9]. Every machine has specific characteristic modes of vibrations that can be distinguished during normal operating conditions. Each of the modes is characterized by its spectrum and a distinguished pattern of relative amplitudes. That is dependent on its mass, system stiffness, fitting tolerances, friction levels, and other parameters typical of the system [10]. Several researchers noted that in many cases, there exist a direct one-to-one relationship between the cause of the defect and the frequency content and amplitude of the vibration signal. In recent years, these vibration analysis applications have been applied to complicated devices that incorporate a large number of moving parts such as reciprocating machines, gear boxes transmissions, and also in a small number of applications involving internal-combustion engines as done by [11]. To keep vibrations under control it is essential to understand the basics and the main sources of engine vibrations. Vibration characteristics can be divided into two types: forced vibration and free vibration. Forced vibration relates to problems such as mass unbalance, misalignment, and excitation of electrical or mechanical nature. Free vibration is a self-excited phenomenon that is dependent on the geometry mass, damping of the system, acoustic resonance, and aerodynamic or hydrodynamic excitation [12]

4. Wavelet transforms method and multi-resolution analysis:

4.1 Wavelet transforms method:

There are many signal analysis methods have been used for fault diagnostics. Among which of them, Fourier fast transforms (FFT) is one of the most widely used and well-established methods [13]. Unfortunately, the FFT-based methods are unsuitable for non-stationary signal analysis and are not able to reveal the inherent information of non-stationary signals. Because of the disadvantages of the FFT analysis, it is necessary to find supplementary methods for non-stationary signal analysis.

Time–frequency analysis is the most popular method for the analysis of non-stationary signals, such as the Choi–Willams distribution (CWD), cone-shaped distribution (CSD) and Wigner–Ville distribution (WVD) [14]. These methods perform a mapping of one-dimensional signal *x(t)* to a two-dimensional function of time and frequency TFR*(x: t,ω.* Therefore, are able to provide true time–frequency representations for the signal *x(t)*. But each of the time– frequency analysis methods have suffered some problems. In order to overcome these disadvantages, many improved methods have been proposed, such as wavelet transforms, etc.. The past decade has witnessed an explosion of activity in wavelet analysis. Wavelets provide a powerful and remarkably flexible set of tools for handling fundamental problems in science and engineering. The wavelet transform has emerged as an efficient tool to deal with non-stationary signals such as vibration signal waveforms [15]. It offers simultaneous interpretation of the signal in both time and frequency domain, which allows local transient or intermittent components to be exposed. Wavelet transform can be continuous or discrete. The continuous wavelet transform (CWT), reveals more details about a signal but its computational time is enormous. For most applications, however, the goal of signal processing is to represent the signal efficiently with fewer parameters and less computation time. The discrete wavelet transform (DWT), can satisfy these requirements. One advantage of wavelet analysis is the ability to perform local analysis [16]. Wavelet analysis can reveal signal aspects that other analysis techniques missed, such as trends, breakdown points and discontinuities. The wavelet analysis calculates the correlation between the signal under consideration and a wavelet function $\psi(t)$. The similarity between the signal and the analyzing wavelet function is computed separately for different time intervals. In comparison to the Fourier transform, the analyzing function of the wavelet transforms can be chosen with more freedom, without the need of using sine-forms. A wavelet function is a small wave, which must be oscillatory in some way to be discriminating between .[different frequencies [17

4.1.1 Continuous wavelet transforms:

Continuous wavelet transform signal $x(t)$ is defined as [18]:

$$x_{wt}(\tau, s) = \frac{1}{\sqrt{|s|}} \int_{-\infty}^{\infty} x(t) \psi^{*}\left(\frac{t-\tau}{s}\right) dt. \qquad [1]$$

The coefficients transformed signal $X_{wt}(\tau, s)$ is a function of the translation parameter or the time parameter τ (i.e. the mother wavelet) and the scale parameter s (also called father wavelet). The mother wavelet is denoted by ψ(t), the * indicates that the complex conjugate is used in case of a complex wavelet. The signal energy is normalized at every scale by dividing the wavelet coefficients by $1/\sqrt{|s|}$ [18]. This ensures that the wavelets have the same energy at every scale or the reason for choosing the factor $1/\sqrt{|s|}$ in the above equation is to keep the energy of the wavelets constant.

Where $\psi(t)$, is the mother wavelet and other wavelets can be calculated as :follow

$$\psi_{s,\tau}(t) = \left(\frac{1}{\sqrt{s}}\right)\psi\left(\frac{t-\tau}{s}\right)dt \qquad [2]$$

Where s and τ are the dilation parameter and translation parameters respectively, $s \in R^{+} - \{0\}, \tau \in R$ [19]. The discrete wavelet transform (DWT), instead of (CWT), is used in this study [20]. Calculations are made for a chosen subset of scales and positions. Before long, Daubechies constructed orthogonal wavelet bases compactly supported in a simple but ingenious way. In addition, Daubechies has done many researches on wavelet frames that allow more liberty in the choice of the basis wavelet functions at a little expense of some redundancy. Daubechies, along with Mallat, is therefore credited with the development of the wavelet from continuous to discrete signal analysis. In the discrete wavelet (DWT) formalism, the scale s and the time τ are discretised as following:

$$s = s_0^m,\ s_0 > 0 \text{ And } m \in Z \quad \tau = n s_0^m \tau_0 \qquad [3]$$

Where *m* and *n* are integers. Therefore, the continuous wavelet function $\psi(t)$ becomes the discrete wavelets given by

$$\psi_{m,n}(t) = s_0^{-m/2}\psi\left(s_0^{-m}t - n\tau_0\right). \qquad [4]$$

The discretisation of the scale parameter and time parameter leads to the discrete wavelet transform, defined as

$$X_{wt}(m,n;\psi) = s_0^{-m/2}\int x(t)\psi^{*}\left(s_0^{-m}t - n\tau_0\right)dt. \qquad [5]$$

Different from the STFT, the wavelet transform can be used for multi-scale analysis of a signal through dilation and translation, so it can extract time–frequency features of a signal effectively. Therefore, the wavelet transform is more suitable for the analysis of non-stationary signals [21]. Now, the wavelets have obtained great success in machine fault diagnostics for its many distinct advantages, not only for its ability in the analysis of non-stationary signals. The wavelet coefficients in the different frequency bands of the DWT can be processed in several ways. By adjusting the wavelet coefficients the reconstructed signal of the synthesis filter bank can be changed in comparison to the original signal. This gives the DWT some attractive properties over linear filtering. Compared to the CWT, the DWT is simply to compute, and its coefficients are easier to interpret since no conversion from scale to frequency has to be made. This scheme was conducted by computing the so-

called approximations and details coefficients. The approximations coefficients are the high-scale, low frequency components of the signal. The details coefficients are the low-scale, high-frequency components. The (DWT) coefficients are computed using the equation:

$$x_{s,\tau} = x_{j,k} = \sum_{n \in Z} x[n] g_{j,k}[n]$$ [6]

Where $s = 2^{j}, \tau = k2^{j}, j \in N, k \in Z$

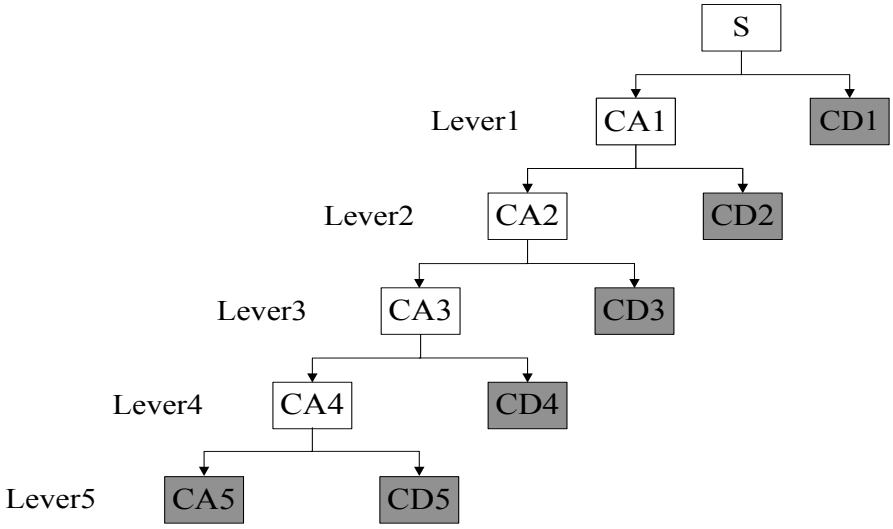
The wavelet filter g plays the role of ψ (t).The decomposition (- cess can be iterated, so that one signal is broken down into many lower resolution components. This is called the wavelet decomposition tree [21]. For detection of transients a multi-resolution analysis tree based on wavelets has been applied [22]. Figure 4 below shows the structure tree of 5-level multi-resolution decomposition. Every one of the wavelet transform sub-band was reconstructed separately from each other, so as to get k+1 separated components of a signal *x[n]*. The MATLAB multires function [23] calculates the approximation coefficients to the 2^k scale and the detail coefficients signals from the 2^1 to the 2^k scale for a given input signal. It uses the analysis filters low-pass and high-pass to synthesis those filters again to get the original signal. The decomposition can be halted at any scale, with the final smoothed output containing the information of all the remaining scales.

4.1.2 Multi-resolution analysis:

The discrete wavelet analysis is based on the concept of multi-resolution analysis (MRA) introduced by [24]. With the (MRA), a signal is decomposed recursively into a sum of details and approximations coefficients at different levels of resolution. From the low-pass filter, we get a vector of approximation coefficients (CA1). That represents an estimation of original signal with half resolution. From the high-pass filter, we obtain a vector of detail coefficients (CD1). That contains the details of the signal. The vector (CA1) can be further decomposed to form a new vector of approximation coefficients (CA2) and a new vector of detail coefficients (CD2). With the increase of the decomposition level, less information will be included in the approximation coefficients. The lost information between approximation coefficients of too successive decompositions is encoded into the detail coefficients. This process can be iterated to level N. In case of this study iterated to level 5 and db order 5. As a result, a vector of approximation coefficients and a series of vectors of detail coefficients are accomplished that forms the DWT coefficients. . For instance, if F_s is the sampling frequency, then the approximation of a level-N of the DWT decomposition corresponds to the frequency band $\left(0, \frac{F_s}{2^{N+1}}\right)$, whereas the detail covers the frequency range $\left(\frac{F_s}{2^{N+1}}; \frac{F_s}{2^N}\right)$, . The relation of 5-level multi-resolution decomposition at original signal S is noted as S = CA5+CD5+CD4+CD3+CD2+CD1

Where D1 to D5 denoted the first to fifth the higher-frequency signal while, A5

denotes the lowest frequency signal. The signal can be conveniently reconstructed by inverse discrete wavelet transform (IDWT).



As shown in figure 5 at each stage of the (MRA) the signal is passed through a high-pass filter (called the scaling filter) denoted as H. While low-pass filter (called the wavelet filter) denoted as G. The filters *H* and *G* are the decomposition filters. At the same time, the filters H_0 and G_0 are the re-construction filters. The process of reconstructing the approximations $CA_i(t)$ and details $CD_i(t)$ is presented in Figure 6.

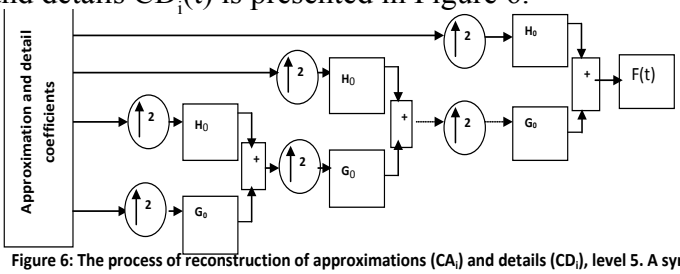


Figure 6: The process of reconstruction of approximations (CA_i) and details (CD_i), level 5. A symbol ↑2 represent dyadic up-sampling.

The wavelet coefficients thus obtained can then be used for the purposes of signal de-noising and compression [25].

5. Signal de-noising:

When a signal was collected from the diesel engine head, it is frequently contaminated by noise. The term noise refers to any undesired change that has altered the values of the original signal. The simplest model for acquisition of noise by a signal is additive noise, which has the form: Contaminated signal = original signal + noise. Noise reduction, as an integral part of signal estimation, has been studied for many years in diverse fields such as vibration signals. The principle of de-noising method using DWT is that the wavelet coefficients belonging to the noise at each scale must be removed, while keeping the valuable signal. Finally, the reconstruction of decomposed and de-noised signal can be processed by reciprocity property.

5.1 The threshold de-noising method:

For signal de-noising, it has been shown that threshold the wavelet coefficients of a noisy signal, allows to restore the smoothness of the original signal. Since the beginning of using wavelet transforms in signal processing, it has been noticed that wavelet threshold is of considerable interest for removing noise from signals. The method consists of decomposing the data into an orthogonal wavelet basis, to suppress the wavelet coefficients smaller than given amplitude; therefore, to transform the data back into the original domain. In this research investigates the use of discrete wavelets for de-noising diesel engine head vibration signals. Because of the large bandwidth of the diesel engine head systems, the vibration signal is usually contaminated by noise coming from various sources such as the crank mechanism, pressure pulses from gas, fuel or air flow, valves, gearwheels, an unbalanced turbocharger, and so on. De-noising the diesel engine head vibration signals before performing any data analysis is very important in order to enhance the detection performance of the diesel engine faults and to get correct depth results [26]. Removing noise components by threshold the wavelet coefficients is based on the observation that in many signals such as diesel engine head vibration signals; energy is mostly concentrated in a small number of wavelet dimensions. The coefficients of these dimensions are relatively large compared to the other dimensions or to noise, which has its energy spread over a large number of coefficients. Hence, by setting smaller coefficients to zero, one can nearly optimally eliminate noise while preserving the important information of the original signal [27].

5.2 Hard and Soft Thresholding:

There are two standard threshold techniques exist: soft threshold (shrink or kill), and hard threshold (keep or kill). The soft and hard thresholds' methods are used to estimate wavelet coefficients in wavelet threshold de-noising [28]. The simplest threshold technique is the hard threshold, where the new values of the details coefficients, $cd^{\wedge}(t)$ are found according to the following:

$$cd^{\wedge} = \begin{cases} cd(t) & if \left|cd(t)\right| > \theta \\ 0 & if \left|cd(t)\right| \le \theta \end{cases} \qquad [7]$$

Where: $cd(t)$ is the details coefficients, and θ is the threshold level.
Another method of threshold is the soft threshold, where the new details coefficients are given by the following:

$$cd^{\wedge} = \begin{cases} sign(cd(t))(|cd(t)| - \theta) & if\ |cd(t)| > \theta \\ 0 & if\ |cd(t)| \le \theta \end{cases}$$

Where *sign()* is the sign function. [8]

The threshold θ can be estimated as follows: $\theta = \sigma\sqrt{2long(N)}$ [9]
Where: N is the length of threshold coefficients and σ characterizes the noise level. These and other methods of threshold selection are described in [30]. In order to get the de-noised signal, the new details coefficients, $cd^{\wedge}(t)$ are used in the signal reconstruction process instead of the original coefficients CD (t). Figures 7 and 8 illustrated the difference between the hard and soft thresholds de-noising methods respectively; these methods have been widely used in data processing. The de-noising procedure is summarized in Figure 9.

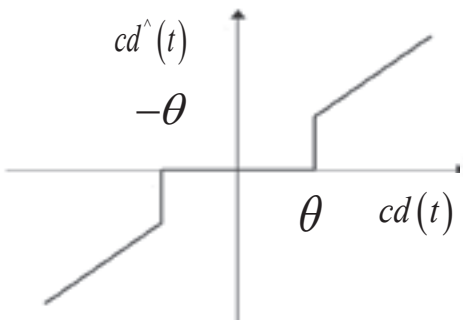


Figure 7: Hard Threshold De-noising

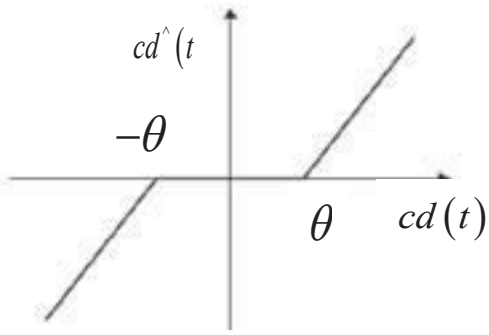


Figure 8: Soft Threshold De-noising

Figure 9: DWT de-noising procedure.

When the signal to noise ratio is greater than the root mean square error, the signal is closer to the original signal and the noise was reduced or removed.

Choose $x(n)$ taken to the original signal, $\hat{x}(n)$ for the signal after de-noising. SNR formula is defined as:

$$SNR = 10\log\left[\frac{\sum_n x^2(n)}{\sum_n \left[x(n) - \hat{x}(n)\right]^2}\right]$$

[10]

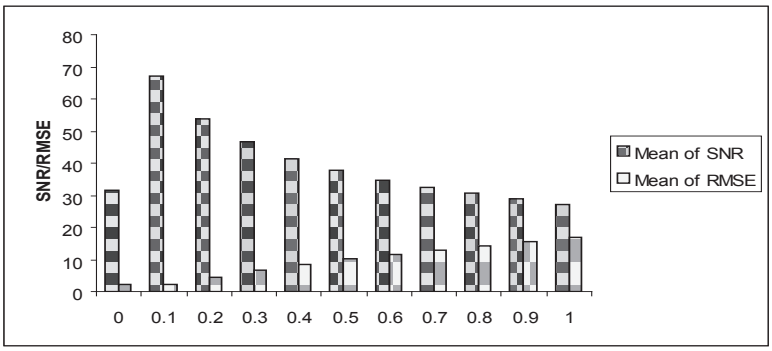
Root mean square error formula is defined as:

$$RMSE = \sqrt{\frac{1}{N}\sum_n \left[x(n) - \hat{x}(n)\right]^2}$$

[11]

5.3 Selection of the optimum threshold level for the de-noising process:

The selection of the threshold level that ranges from 0.0-1.0 plays an important role in the de-noising process. That is manifested by the cancellation of the noise. Therefore, selection of the appropriate value of θ is very important. In order to use a suitable mother wavelet and decomposition level N for de-noising signal, several tests on the selected samples (4096 samples) were done. From those tests, it was cleared that the best mother wavelet and level N are sym5 and level 5 respectively. To select the appropriate threshold level for de-noising process comparing the average of signal to noise ratio (SNR) and root mean square error (RMSE). The results are plotted in histogram form below. Knowing that the difference between SNR and RMSE is very big, so to compare SNR and RMSE, we multiplied the RMSE by 10 (RMSE × 10), as shown below in Figure 10.



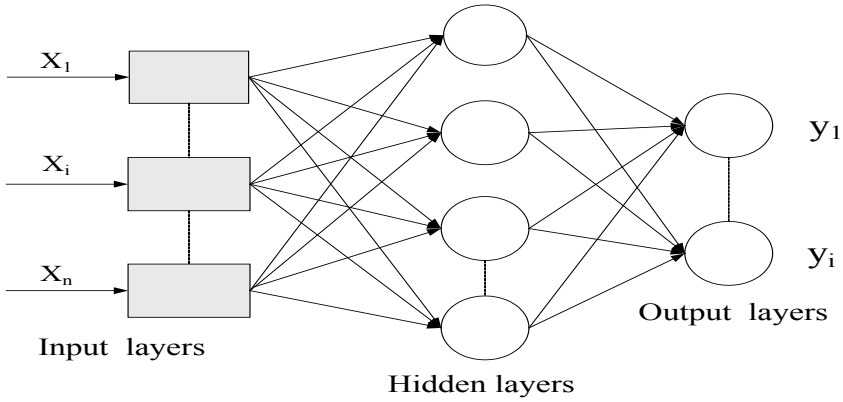
From figure 10 clearly, when θ = 0.1 the average of SNR was 67.0272, which is the biggest value, that is also greater than that of the RMSE. This means that the signal is closer to the original signal, and the noise was reduced or removed. So this θ =0.1 is considered as the best hard threshold level to proceed for de-noising process.

6. Choice of mother wavelet and wavelet decomposition level:

There are many different mother wavelets are playing an important role in the impact of the noise cancellation [29]. The selection of mother wavelet is one of the main factors to maintain the important data in the wavelet domain. According to [30] they stated that, the effectiveness of the wavelet analysis is largely influenced by the choice of the mother wavelet, decomposition level and the noise cancellation. The choice of the appropriate mother wavelet depends on the nature of the signal and the type of information to be extracted from the signal. In order to select the best of the mother wavelet and decomposition level of the wavelet function in this study, we have done many several tests in many types of wavelet functions such as Daubechies, Symlet, Haar and Coiflet wavelet families. The result showed that the selected mother wavelet types have the greatest value of the SNR and this also greater than that of the RMSE. The `db5' mother wavelet and wavelet decomposition level 5 have the best performance on more than others do. So that we applied them in this research studied.

7. Back Propagation neural network:

In recent years, artificial neural network (ANN) has received great attention to many aspects of scientific research and has been applying successfully in various fields such as chemical processes, engineering, digital circuitry and control systems. (ANN) provide a mechanism for adaptive pattern classification, even in unfavorable environments; it can still have robust classification [31]. It should be stressed that choosing a suitable ANN architecture is vital for the successful application of ANN. To date, the most popular ANN architecture is the backward propagation neural network (BPNN) [32]. Furthermore, neural networks are capable of performing fault classification at hierarchical levels. Based on learning strategies, ANN falls into two categories: supervised and unsupervised. The BPNN is a supervised network. Figure 11 shows a model of backward propagation neural network. Each input node is connected to a hidden layer node, and each hidden node is connected to an output node in a similar way. This makes the BPNN a fully connected network. The outputs are compared with the desired target values, and an error is produced. Then the weights are adapted to minimize the error. Since the desired target, values are known; this is a supervised learning process.



The input values (input data) are fed to the neurons in the so-called input layer in the left part of figure 11. The input values are processed within the individual neurons of the input layer. Then the output values of these neurons are forwarded to the neurons in the hidden layer. The arrows indicate connections from the input nodes to hidden nodes. Along which the output values of the input nodes are passed on to the hidden nodes. Either these values obtained as inputs by the hidden nodes are again processed within them and passed on to the output layer or to the next hidden layer (sometimes there can be more than one hidden layer). Each connection has an associated parameter indicating the strength of this connection, the so-called weight. By changing the weights in a specific manner, the network can "learn" to map patterns presented at the input layer to target values of the output layer. The description of the procedure, by which this weight adaptation is performed, is called learning or training algorithm. Sometimes, so-called bias units are also present in the neural network. These are neurons with the property that they always produce a +1 at the output [33]. The back propagation algorithm is the most commonly used ANN learning technique. For a three-layer network with *n* input, *h* number hidden neurons and *m* output neurons, the number of neurons in hidden layer would be obtained as fallow: $h = \sqrt{n * m} + c$ [12]

Calculate the hidden node output y_i as follows:

$$y_i = f\left(\sum_j w_{ij} x_j - \theta_j\right) \quad [13]$$

Where: x_j The input to the input node, w_{ij} input layer to hidden layer connection weights, θ_j threshold for the hidden layer nodes. Calculate Output node of the output o_i as follow:

$$o_i = f\left(\sum_i T_{ij} y_i - \theta_i\right) \quad [14]$$

Where: T_{ij} is the hidden layer to output layer connection weights, θ_i threshold for the output layer nodes.

Calculate error control as follow: $E = \sum_{k-1}^{p} e_k < \varepsilon$ [15]

$$e_k = \sum_{l-1}^{L} \left| t_1^{(k)} - o_l^{(k)} \right|^2$$ [16]

Where: E error for all samples, e_k error for one sample; p is the number of samples, n output nodes, t_l is the desired output of output node:

Calculate error value δ as follow: $\delta_1 = (t_1 - O_l) \cdot O_l \cdot (1 - O_l)$ [17]

Weight correction can be obtained as follow: $T_{li}(k+1) = T_{li}(k) + \eta \delta_l y_i$ [18]

Threshold correction can be obtained as follow: $\theta_l(k+1) = \theta_l(k) + n\delta_1$ [19]

Hidden layer node revised as follow:

Error can be obtained as follow: $\delta_i^{'} = y_i(1 - y_i) \sum \delta_l T_{li}$ [20]

Weight correction can be obtained as follow: $w_{ij}(k+1) = w_{ij}(k) + \eta^{'} \delta_i^{'} x_j$ [21]

Threshold correction can be obtained as follow: $\theta_i(k+1) = \theta_i(k) + \eta^{'} \delta_i^{'}$ [22]

8. Based on support vector machine signal pattern recognition system

Support vector machine (SVM) is based on Vapnik–Chervonenkis theory (VC-theory) that recently emerged as a general mathematical framework for estimating (learning) dependencies from finite samples. This theory combines fundamental concepts and principles related to learning, well-defined formulation, and self-consistent mathematical theory. Moreover, the conceptual framework of VC-theory can be used for improved understanding various learning methods developed in statistics, neural networks, signal processing and so on. Based on VC, the bounds on the generalization performance are optimized using a training algorithm, [34] proposed that automatically maximizes the margin between the training patterns and the decision boundary. This algorithm constructs, and then searches the separating hyper-planes with maximum margin by transforming the problem description into dual space by Lagrangian. SVM is successfully applied in optical character recognition problems with good generalization ability compared with

two-layer back-propagation neural network. The other success is also in [35] stated that the SVM was better than linear classifier. In machine condition monitoring and fault diagnosis problem, SVM is employed for recognizing special patterns from an acquired signal. Then these patterns are classified according to the fault occurrence in the machine. SVM is introduced into machines fault diagnosis due to its high accuracy and good generalization for a smaller number of samples.

8.2 Construction of SVM algorithm is as follows:

Support vector machines are a useful classification method [34]. Given data input x_i (i = 1, 2, 3 … L), L is the number of samples. The samples are assumed to have two-class namely positive class and negative class. Each of classes associates with labels be $y_i = 1$ for positive class and $y_i = -1$ for negative class, respectively. In the case of linearly data, it is possible to determine the hyper-plane f(x) = 0 that separates the given data or linearly separable training set of $|x_i, y_i|, x_i \in R^n, y_i = \{+1,-1\}(i = 1,2,...,l)$. There are real number sequences even (w,b) satisfy the conditions:

$$\begin{cases} w.x_i + b \geq 1 & (y_i = +1) \\ w.x_i + b \leq -1 & (y_i = -1) \end{cases} \qquad [23]$$

Classification function from the above conditions is the following:

$$f(x) = sign(w \cdot x_i + b) \qquad [24]$$

The separating hyper-plane that creates the maximum distance between the plane and the nearest data, i.e., the maximum margin, is called the optimal separating hyper-plane. Taking into account the noise with slack variables g_i and the error penalty C, The optimal hyper-plane separating the data can be obtained as a solution to the following

optimization problem:

$$\text{Minimize } D_{\min} = \frac{1}{2}\|w\|^2, \quad D_{\min} = \frac{1}{2}\|w\|^2 + C\sum_{i=1}^{l} g_i \qquad [25]$$

Subject to $y_i(w.x_i + b) \geq 1 \quad (i = 1,2,..l)$

The calculation can be simpli

condition into the equivalent Lagrangian dual problem, which will be

$L(w,b,a)=\frac{1}{2}\|w\|^2-\sum_{i=1}^{l}a_i\left[y_i\left(w.x_i+b\right)-1\right]$ (26), Which Lagrange multiplier $a_i \geq 0$.

The task is minimizing Eq. (26) with respect to *w* and *b*, while requiring the derivatives of *L* to *a* to vanish. At an optimal point, we have the following saddle-point

equations: $\frac{\partial L}{\partial w}=0, \quad \frac{\partial L}{\partial b}=0,$ [27]

This is replaced into form: $w=\sum_{i=1}^{l}a_i y_i x_i, \quad \sum_{i=1}^{l}a_i\, y_i=0\left(a_i \geq o\right)$ [28]

From Eq. (28), we find that *w* is contained in the subspace spanned by the x_i. Using substitution Eq. (iii) into Eq. (26), we obtain the dual quadratic optimization prob-

lem: Maximize $L(a)=\sum_{i=1}^{l}a_i-\frac{1}{2}\sum_{ij=0}^{l}a_i a_j y_i y_j x_i.x_j$ [29]

Subject to $a_i \geq o, \quad i=1,...,l, \quad \sum_{i=1}^{l}a_i\, y_i=0.$ [30]

Thus, by solving the dual optimization problem, one obtains the coefficients a_i, which is required to express the *w* to solve Eq. (25). This leads

to non-linear decision function. $f(x)=sign\left(\sum_{ij=1}^{l}a_i y_i x_i.x_j+b\right)$ [31]

SVM can also be used in non-linear classification tasks with application of kernel functions. The data to be classified is mapped onto a high-dimensional feature space, where the linear classification is possible. Using the non-linear vector

function $\varphi(x)=\left(\phi_1(x),...,\phi_l(x)\right)$ to map the *n*-dimensional input vector *x* onto *l* dimensional feature space, the linear decision function in dual form is given by

$$f(x)=sign\left(\sum_{ij=1}^{l}a_i y_i\left(\phi(x_i).\phi(x_j)\right)+b\right) \quad [32]$$

Working in the high-dimensional feature space enables the expression of complex functions, but it also generates the problem. Computational problem occurred due to the large vectors, and the over-fitting exists due to the high-dimensionality. The

latter problem can be solved by using the kernel function $K\left(x_i, x_j\right)$. Kernel is a function that returns a dot product of the feature space mappings of the original data points, stated as $K\left(x_i, x_j\right) = \left(\phi\left(x_i\right).\phi\left(x_j\right)\right)$. When applying a kernel function, the learning in the feature space does not require explicit evaluation of ϕ and the decision function will be: $f\left(x\right) = sign\left(\sum_{ij=1}^{l} a_i y_i K\left(x_i, x_j\right) + b\right)$. [33]

Any function that satisfies Mercer's theorem [36] can be used as a kernel function to compute a dot product in feature space. There are different kernel functions used in SVM, such as linear, polynomial and Gaussian radial basis function (RBF). The selection of the appropriate kernel function is very important, since the kernel defines the feature space in which the training set examples will be classified. The definition of legitimate kernel function is given by Mercer's theorem. In this study, linear, polynomial and (RBF) were evaluated and formulated as follows: Linear kernel: $K(x_i, x_j) = x_i \cdot x_j$ [34]

Polynomial kernel: $K(x_i, x_j) = (x_i \cdot x_j + 1)^3$ [35]

Radial basis function (RBF) kernel: $K(x_i, x_j) = \exp\left\{ -\left|x_i - x_j\right|^2 \Big/ 2\delta^2 \right\}$ [36]

Here δ is kernel parameter.

9. Results and discussion:

9.1 Wavelet analysis on Cylinder Head Vibration Signal:

Original cylinder head vibration signal not only included low-frequency signal, but also includes complicated high-frequency signal. Consequently, it is difficult to discriminate between healthy and faulty behaviors from the original signals directly, especially in high-speed segment. Therefore, the fault can be clearly distinguished after decomposed the original signals. When a defect occurs, the engine vibration accelerates signal transfer function will change in different frequencies and amplitudes. Therefore, that, output signal energy distribution will change. For example, some frequency-domain signals are suppressed, and other's frequency-domain signals are enhanced, a corresponding resulting of that decrease or increase in an energy. In this study, DWT decomposition is applied to the vibration data for normal and abnormal condition, using mother wavelet Daubechies (db5) and decompo-

sition level 5. The original signal (S) was decomposed into six components: fifth level approximation CA5 and five-level details from CD1 to CD5. The frequency sub-bands corresponding to each component of the signal are shown in Table 2.

Table 2: Frequency sub-bands for sixth level DWT decomposition.

Fr. bands	1	2	3	4	5	6
Fr. range ((Hz	0-136	136-264	264-519	519-1030	1030-2052	2052-4096
	CA5	CD5	CD4	CD3	CD2	CD1

Fr. = frequency

9.2 Characteristics of the signal energy and fault detection

The analysis of the energy characteristics of the signal can be used for the diesel engine fault detection. Therefore, that the energy extraction from each frequency sub-band of normal and abnormal conditions as a feature of engine fault diagnosis. Any method developed for this purpose should be highly accurate. There is an approach based on the fact that faults are translated into transient of low and high-frequency phenomena in the vibration signal. Consequently, the abnormal behavior can be detected by analyzing the energy contained in those frequencies. It was found that, when this approach is applied to the sub-band frequency, the energy in the sixth band is always the highest if the condition is normal while it will be highest in the first band if the condition is abnormal. This result agreed with [37], when they applied wavelet decomposition for the detection and diagnosis of faults in rolling element bearings. From this view, we could efficiently distinguish between normal and abnormal conditions behavior by comparing the energy of each sub-band. Figure12 below showed the results of the energy contained in the frequency sub-bands 1, 2, 3, 4, 5 and 6 for vibration data of normal and abnormal conditions.

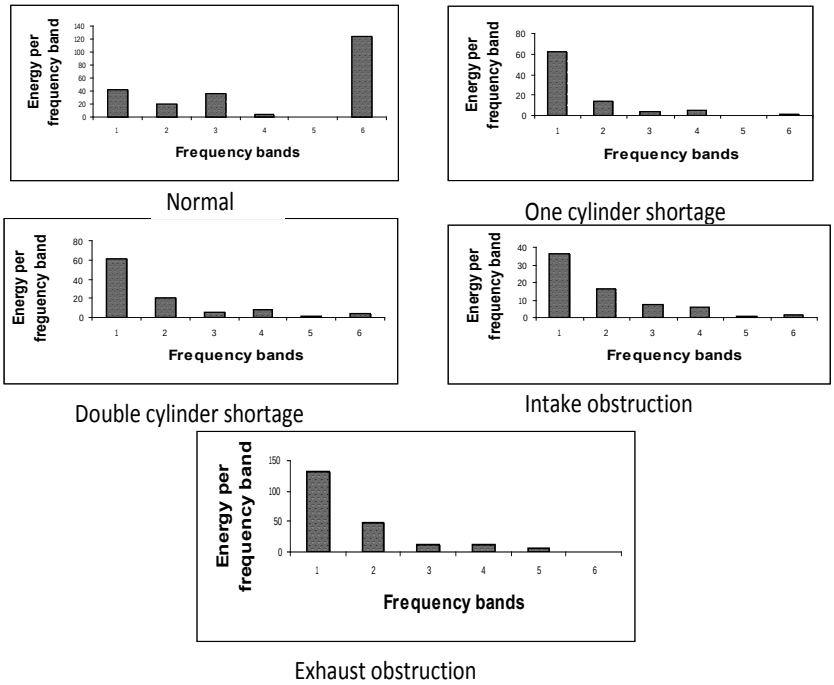


Fig. 12: Average energy contained in the frequency sub-bands 1, 2, 3, 4, 5 and 6 for vibration data captured on a surface of the cylinder head of the 295 diesel engine.

9.3 Back-propagation network design:

The BP model used in this study is included in MATLAB Neural Network Toolbox. In this

application, the numbers of X_i inputs are associated with the number of details coefficients extracted from discrete wavelet analysis. The number of hidden layers and the number of neurons in the hidden layer are generally application dependent. For this study, one hidden layer was used for whole the test, while the numbers of neurons in this layer were 19 to observe the change in classification accuracy.

There were five y_i outputs, which were associated with the number of diesel engine faults conditions. The output from the network is binary. That is, each output node is either zero or one. Create a BP network used “newff” function. The input layer and middle layer of the transfer function is”tansig”. The middle layer and output layer transfer function is “purelin” while, training function is “trainlm”. Weights and threshold value of the BP learning algorithm used the default gradient and descent momentum learning function is “learngdm”. The mean square error for the default performance function “mse” and select the network training

error of 0.001. Five working conditions (exhaust obstruction, intake obstruction, normal, single cylinder shortage and double-cylinder shortages) correspond to the desired output to 10000, 01000, 00100, 00010 and 00001 respectively. For example, that when the output was 10000 recognition results of the exhaust obstruction.

9.4 Features Extracted using SVM and BPNN:

Figure 13 illustrated a comparison of the diagnostic accuracies rates extracted as percentages, using SVM and BPNN on five diesel engine faults condition. They applied them on signal captured from the test diesel engine at different speeds, loads and five faults condition. The experimental results showed that, diagnostic accuracy of BPNN in the fault diagnosis has higher rates than that of SVM for all cases. These results agreed with [38], when he applied artificial neural network and SVM to diagnose the learning disabilities problem for students. His results showed that neural network performs better than SVM. In addition, we can see that the normal condition has the highest accuracies rate about 100% for all conditions. Except for SVM at speed 620 r/min with load zero is a lowest about 40%. Therefore, we can observe that BPNN is the most consistent in all the conditions than SVM. Finally, according to the above results, we can conclude that the BPNN is the excellent method than SVM in fault diagnosis for a diesel engine in our cases conditions.

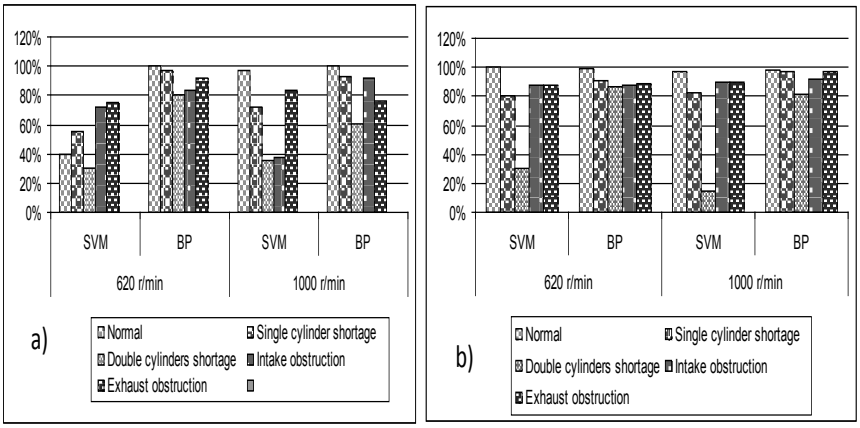


Figure 13: Classification accuracy rate (%) extracted from SVM and BPNN, on the diesel engine data, at different speeds and loads, under five faults condition. a) load 0

9.5 Design and model support vector machine training

Support vector machine on different trainings fault classification has been used in this study. Just as BPNNN model, SVM Toolbox was also used in MATLAB software. In this application, the numbers of X_i inputs associated with the number of details coefficients extracted from wavelet analysis. The numbers of y_i outputs associated with five above-mentioned diesel engine faults conditions. There are two parameters

for an RBF kernel. Parameter c is the error penalty function and the parameter g is the kernel functions. In the "svmtrain" function, c and g are usually given empirically or by any calculation to obtain cross-validation. The goal is to identify good (c, g). Therefore, the classifier can accurately predict unknown data (i.e. testing data). So that usually use the function "svmtrainforclass" for cross-validation to determine the values of c and g. Note that it may not be useful to achieve high training accuracy (i.e. a classifier which accurately predicts training data whose class labels are indeed known). The prediction accuracy obtained from the unknown set more precisely reflects the performance on classifying an independent data set. The cross-validation procedure can prevent the over-fitting problem. The current experiment applied cross-validation data set for two speeds, two loads and five-engine faults condition. Figures 14 and 15 below, showed the results of multi-classification of the optimizations c and g, in two and three-dimensional contour. After running the Matlab program, we found that, when speed is 620 r/min, c = 1.7411, g = 0.32988, and accuracy = 90.33%, while speed is 1000 r/min, c = 16, g = 1.7411, and accuracy = 81%.

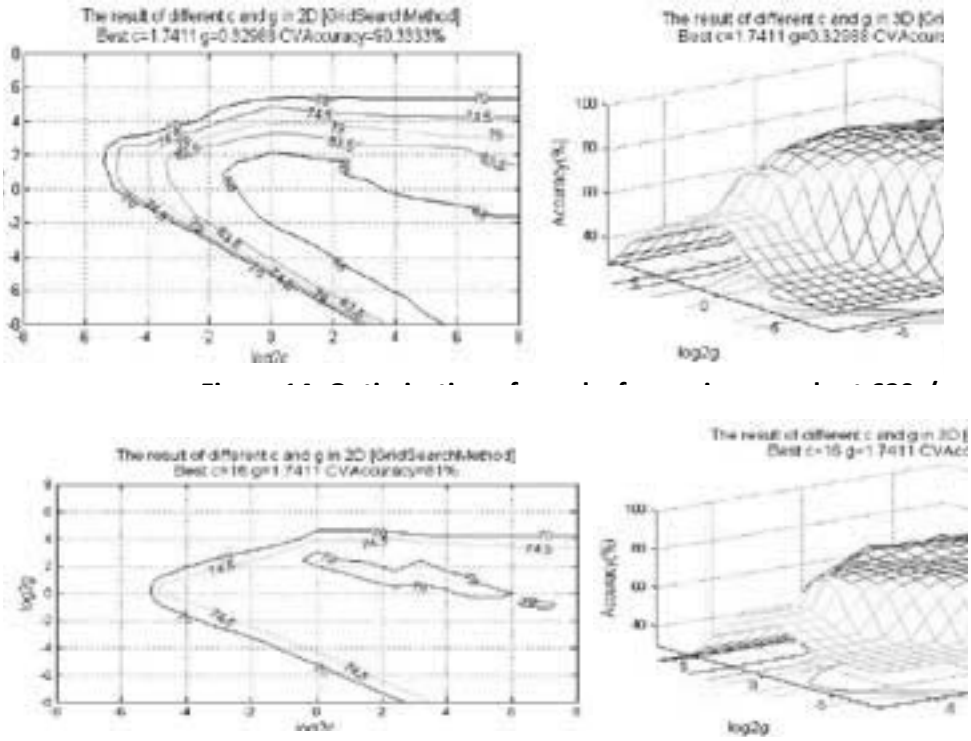


Figure 15: Optimization of c and g for engine speeds at 10(

10. Conclusion:

Diesel engine fault diagnosis depends largely on the feature extraction of signals. This paper showed that, the energy extracted from wavelet analysis techniques could be successfully used in condition monitoring and fault diagnosis of diesel engine faults. Hard threshold was applied. Daubechies (db5) mother wavelet was used. In addition, it presented BPNN and SVM techniques for detection of the diesel engine faults by classification accuracy rate. The results showed that, the potential application of these techniques for developing efficient detection strategies to prevent catastrophic failure and reduced operation cost. In the classification, the experimental results showed the BPNN was effective in fault diagnosis for internal combustion engine with various fault conditions. For further research on the diesel engine by the choosing of an appropriate wavelet function can increase the accuracy of faults detection.

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Effect of Diammonuim Phosphate and Chicken Manure Fertilization on Some Soil Physical Properties, Growth and Yield of wheat (Triticum aestivum L.) at El Multaga Area, Northern State, Sudan

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Abstract

A field experiment was executed during winter seasons of the years 2011/12 and 2012/13, at the demonstration farm of the National Institute of Desert Studies – University of Gezira, new Hamdab scheme - Northern State of Sudan, to study the effect of diammonuinm phosphate (DAP) and chicken manure (CM) fertilization and their interaction on wheat (Tritium aestivum L.) growth, yield and some soil physical properties. The treatments were arranged in a randomized complete block design(RCBD) with four replicates consisted control, diammonuim phosphate(DAP) 100Kg ha^{-1} alone, application of chicken manure (4 ton ha^{-1}) alone and (DAP)100Kg ha^{-1}+ 4 ton ha^{-1}(CM) .Result showed that the soil dry bulk density was very highly significantly ($P \leq 0.001$) reduced on the average from 1.79 g cm^{-3} for the control treatment to 1.39 g cm^{-3} in the (CM) with (DAP) treatments, from 1.79 g cm^{-3} to 1.46 g $cm^{-3}$for (DAP) treatment alone and from1.79 g cm^{-3} to 1.42 g cm^{-3} for the application of(CM) alone. While the soil total pore space (porosity) was found very highly significantly($P \leq 0.001$) increased on average from 38 % in the control treatment to 50.3% for the (CM+DAP), 38% to 47.8% for (DAP) treatment alone and from 38% 48.7% in response to application of the(CM). Also, the effects of the interaction of (CM+DAP), showed highly significant ($P \leq 0.01$) increased in the soil moisture percentage on the average from 9.5% in the control to 18%,9.5 to 16.5% for (DAP) treatment alone and from 9.5% to 16.4% for the chicken manure application alone in the top soil (30 cm soil depth). Results indicated that there were significant ($P \leq 0.05$) differences on plant height (cm), number of seeds/spike, thousand seed weight

(gm), straw yield and harvest index in both seasons and highly sig- (nificant ($P \leq 0.01$) differences on number of tillers m^{-2}, grain yield ton/ ha) in both seasons for the appli- (ton/ ha) and biological yield .cation of chicken manure and diammonuim phosphate fertilizers

Key Words: Diammonuim Phosphate fertilizer- Chicken Manure- Wheat- sudan

مستخلص:

نفذت التجربة الحقلية خلال الموسمين الشتوي للأعوام (2012) و 2013) في الحقل الإيضاحي للمعهد القومي لدراسات الصحراء – جامعة الجزيرة ، مشروع الحامداب الجديدة الزراعي – الولاية الشمالية–السودان و ذلك لدراسة تأثير سماد ثنائي فوسفات الامونيوم وسماد مخلفات الدواجن علي نمو وإنتاجية القمح وبعض الخصائص الفيزيائية للتربة. وزعت المعاملات عشوائيا بتصميم القطع العشوائية الكاملة في أربعة مكررات وتحتوي المعاملات علي الشاهد وسماد ثنائي فوسفات الامونيوم بمعدل (100كجم/هكتار) ومخلفات الدواجن بمعدل(4كجم/ هكتار) ومعاملة خليط سمادي مخلفات الدواجن وثنائي فوسفات الامونيوم (الداب). أظهرت النتائج أن الكثافة الظاهرية للتربة تناقصت بمعنوية عالية جدا($P \leq 0.001$) وبمعدل من1.79 جم سم$^{-3}$ للشاهد إلي 1.39جم سم$^{-3}$في معاملة خليط سمادي ثنائي فوسفات الامونيوم ومخلفات الدواجن ومن 1.79الي 1.46 جم سم$^{-3}$في معاملة سماد ثنائي الفوسفات ومن 1.79الي 1.42اجم سم$^{-3}$ في معاملة سماد الدواجن. بينما شوهدت زيادة معنوية عالية جدا ($P \leq 0.001$) في الفضاء المسامي الكلي للتربة (المسامية) بمعدل38% في الشاهد إلي 50.3% في معاملة خليط سمادي ثنائي فوسفات الامونيوم ومخلفات الدواجن ومن 38%إلي 48.7% في معاملة سماد ثنائي فوسفات الامونيوم ومن 38 إلي 47.8% في معاملة مخلفات الدواجن وأيضا شوهد التأثر علي النسبة المئوية لمحتوي الرطوبة لخليط سمادي ثنائي فوسفات الامونيوم ومخلفات الدواجن بزيادة معنوية عالية($P \leq 0.01$) من 9.5% للشاهد الي18% ومن 9.5%إلي 16.5 %في معاملة سماد ثنائي فوسفات الامونيوم ومن 9.5% إلي 16.4% لمعاملة سماد الدواجن. أظهرت النتائج فروق معنوية ($P \leq 0.05$) في طول النبات (سم)، عدد الحبوب في السنبلة،وزن الالف حبة (جم) إنتاج التبن ومؤشر الحصاد للموسمين وإلي اختلافات عالية المعنوية($P \leq 0.01$) علي عدد السنابل م$^{-2}$، عدد الخلف م$^{-2}$، إنتاج الحبوب(طن/ هكتار) والإنتاج الحيوي (طن/ هكتار) خلال الموسمين نتيجة لتطبيق خليط سمادي مخلفات الدواجن وثنائي فوسفات الامونيوم.

الكلمات المفتاحية : سماد ثنائي فوسفات الامونيوم– سماد مخلفات الدواجن– القمح–السودان.

Introduction

Wheat (TriticumaestivumL.) is mainly grown in the Sudan under irrigation, during winter months; its cultivation has recently expanded into latitudes lower than 15° N [1 , 2].

Application of manure in desert plain soil in the Northern Sudan significantly improved the soil chemical properties and minor increased in organic carbon, nitrogen; available phosphorus and potassium were observed Ahmed [3].The soil pH was not affected by the source of organic manure, the poultry manure application on sandy loamy soil in Southwestern Nigeria improved soil chemical properties. It increased soil organic matter, total N, available P, exchangeable Mg, Ca, K and nutrient uptake and lowered exchange acidity [4].

Chicken manure and sewage sludge application on the poor physical and chemical properties of sand dune soil in Elrawakeeb Dry Land Station, Khartoum State, Sudan resulted in very highly significantly increased soil organic carbon, available P, total nitrogen and mineral nitrogen and decreased soil pH [5].

An experiment was conducted in Iraq to study the effects of three different nitrogen fertilizers ammonium sulfate , diammonium phosphate (DAP) and urea in two wheat species and their interaction on plant height, number of tillers, flag leaf area, shoot dry weight, leaf chlorophylls, number of spikes plant-1, thousand seed weight, grain yield, nitrogen and grain protein content. N fertilizers significantly increased all tested parameters of growth, diammonium phosphate (DAP) followed by ammonium sulfate were a more efficient [6].

The aim of this study was to determine the effect of diammonuim phosphate and chicken manure application on agronomic traits of wheat and some soil physical properties.

Materials and Methods:

Description of the Experimental Site:

Field experiments were carried out during two consecutive winter seasons (2012/and 2013) at the National Institute of Desert Studies Research Farm, New Hamdab Scheme, Northern State of Sudan

(latitude 17°55' N and longitude 31°10' E). The climatic zone of the area is described as desert, which is characterized by high temperature in summer, low temperature in winter and low rainfall [7]. The soil of the study area belongs to El Multaga soil series which classified as vertichaplocambids, fine loamy, mixed, supper active and hyperthermic. The soil structure is moderate sub angular blocky. It is non-saline and non-sodic, generally, the soil chemical fertility is low and mostly these soils deficient in nitrogen, phosphorus and organic carbon for optimum yield production of different cultivated crops [8].

Treatments and Experimental Design

The treatments were arranged in completely randomized block design (RCBD) with four replicates. The area of each sub- sub plot was 42 m^2 (6 × 7 m). The experimental units were two meter apart from each other. The treatments were control without fertilizer, diammonuim phosphate with rate of (100 Kg/ ha), chicken manure with rate of (4ton /ha) and (100 Kg /ha) of DAP+ 4ton ha^{-1} of chicken manure.

Soil Physical Analysis:

The soil dry bulk density (ρd) was determined by the core sample method as described [9,10].Soil core was obtained from 0 -15 cm soil depth for each of experimental units at 80 days after sowing (DAS). The soil was oven dried at 105º C for 24 hours, and weighed. The soil dry bulk density (ρd) for all soil samples were calculated in the lab using the equation below:

$$\rho d = \frac{Ms}{Vt}$$

Where:

Ms is a dry soil mass and

Vt is the total soil volume or the core volume.

Measurements of the soil moisture were done at 0 - 30 and 30 - 60 cm soil depth. Soil samples were taken by using an auger. Readings were taken at the field, two days after irrigation at 80 DAS. Gravimetric method was used to determine the soil moisture percentage (Θ) as described below:

$$\Theta = \frac{(Mm - Md)}{Md}$$

Where
Mm is the moist soil mass
Md is the dry soil mass.
The soil total porosity was calculated by following the equation below:

$$TP = 1 - \rho d / \rho s \%$$

TP = soil total porosity
ρd = soil dry bulk density
ρs = soil particle density (taken as 2.65 g cm^{-3})

Soil Amendment:

Chicken manure was manually broadcasted six weeks before planting on the designated experimental units at the rates of 4 ton ha^{-1}. The manure was incorporated into the soil using disk plow. Then the soil was watered and the subsequent watering was carried out at ten- days interval for six weeks before sowing of wheat crop. Diammonium phosphate fertilization (DAP) containing (16% N + 48% P_2O_5) was added at sowing.

Cultural Practices:

Wheat (Triticum aestivum L.) variety Wadi Elneel has been used in this study. Sowing was done manually by digging on 20th of November for both seasons, with seed rate of 120 kg ha^{-1}, at 0.2 m inter-row spacing. The crop was harvested on 20st of March in both seasons. Irrigation was applied according to [11] who concluded that, wheat water requirements per season were 635mm.

Data Collection:

Plant samples were collected randomly from each experimental unit (sub- sub plot) and then growth and yield parameters (Number of plants/m^2,plant height, number of seeds per spike, thousand seeds weight (gm) , number of tillers, biological yield, grain yield (ton ha^{-1}), straw yield(ton ha^{-1}) and harvest index)were determined. Soil data measured by the methods mention above were soil bulk density, soil total porosity and soil moisture content at 80days after sowing.

Statistical Analysis:

Statistical analysis was carried out using a computer software package (MSTAT). Significance of differences among the various characters under study was compared using Duncan's Multiple Range Test (DMRT).

Results and Discussion:

The interaction effects of DAP and chicken manure fertilization on wheat (Triticum aestivum L.) vegetative growth and yield during tow winter seasons are shown in Tables 1and 2.

The results indicated that chicken manure and DAP had significant ($P \leq 0.05$) effects on plant height, number of seeds/spike, thousand seed weight, straw yield and harvest index in both seasons and highly significant ($P \leq 0.01$) differences on number of tillers m^{-2}, grain yield (ton ha^{-1}) and biological yield (ton ha^{-1}) in both seasons But had not significant effect ($P \leq 0.05$) on number of plants/m2 in both seasons.

The results indicated that the application of 4ton ha^{-1} of chicken manure with100 Kg $ha^{-1}$of DAP produced the highest means values of all examined growth and yield attributes in both seasons. Several investigations from different parts of the world reported that addition of chicken manure improved properties of the soil and enhanced growth and yield of wheat [5 ,6].

The results of this study showed that the application of chicken manure improved growth and yield of wheat. As mentioned by [12] who concluded that chicken manure increased wheat growth and yield significantly. Also, the results is in agreement with that of [3] who stated that, chicken manure improved the plant height, number of seeds per spike, number of tillers per square meter, 1000- seeds weight, straw yield, biological yield, grain yield and harvest index.

Table 3. Show the Interaction effects of DAP and chicken manure fertilization on soil bulk density, porosity and soil moisture percentage at 80 DAS during two Seasons.

Soil Bulk Density (ρd):

The results showed that the interaction of chicken manure of (4 ton

ha-1) and DAP of (100 Kg ha^{-1}) reduced the soil bulk density with very highly significant differences ($P \leq 0.001$) as compared to the control during the two seasons. Reduction in soil bulk density in response to manures application had already been mentioned by many researchers [13] who found that organic manure significantly reduced the soil bulk density.

Soil Total Porosity (TP):

The results stated that the interaction of chicken manure of (4 ton ha^{-1}) and DAP of (100 Kg ha^{-1}) increased soil total porosity with very highly significant differences ($P \leq 0.001$) as compared to the control during the two seasons. This result is in conformity with that of [14] and [4] whom reported that the soil total porosity significantly increased in response to poultry manure application.

Soil Moisture Percentage (ϴ %):

The results indicated that the interaction of chicken manure of (4 ton ha^{-1}) and DAP of (100 Kg ha^{-1}) highly significant ($P \leq 0.01$) increased soil moisture content compared with the control. This result is in conformity with that obtained by [13,14] whom found that moisture percentage increased significantly in response to organic manure application.

Table1.Interaction effects of diammonuim phosphate (DAP) and chicken manure (CM) fertilization on wheat (Triticum aestivum L.) vegetative growth during two winter seasons

Parameters	(Plant height (cm			NO. of tillers/m²		NO. of seeds/spike	
Treatments	1st Season	gt Season	2nd Season	1st Season	2nd Season	1st Season	2nd Season
Control	183	66^{c}	72^{c}	55^{c}	59^{d}	33^{c}	32^{c}
DAP	184^{b}	72^{b}	80^{b}	57^{c}	63^{c}	34^{c}	34^{b}
CM	189^{b}	74^{b}	81^{b}	97^{b}	76^{b}	39^{b}	38^{ab}
DAP+CM	207^{a}	83^{a}	91^{a}	108^{a}	95^{a}	48^{a}	41^{a}
SE±	18.8	8.34	8.17	6.09	6.6	3.74	15.5
C.V (%)	16.3	20.6	18.2	13.6	17.3	17.1	16.9
Sig.	NS	*	*	**	**	*	*

Means within columns followed by the same letter(s) are not significantly different at P<0.05 level according to Duncan's Multiple Range Test.

*** and NS indicate significance at P≤0.05 and not significant, respectively.**

Table2. Interaction effects of diammonuim phosphate (DAP)and chicken manure(CM) fertilization on wheat (Triticum aestivum L.) yield during two winter seasons

Parameters	1000-seeds (weight (g		Biological yield ((Ton ha^{-1}		Grain yield ((Ton ha^{-1}		Straw yield ((Ton ha^{-1}		Harvest (%) index	
Treatments	1st Season	2nd Season	1st Season	2nd Season	1st Season	2nd Season	1st Season	2nd Season	1st Season	2nd Season
Control	31^{b}	33^{c}	7.6^{d}	7.2^{d}	0.51^{d}	0.92^{d}	5.2^{c}	4.9^{d}	31^{c}	32^{c}
DAP	34^{a}	35^{b}	9.4^{b}	8.4^{c}	2.1^{c}	1.2^{c}	6.3^{a}	5.5^{b}	33^{b}	34^{b}
CM	35a	37^{b}	8.8^{c}	8.5^{b}	3.1^{b}	3.9^{b}	5.1^{c}	5.4^{c}	38^{a}	36^{ab}
DAP+CM	38^{a}	39^{a}	9.9^{a}	12.3^{a}	3.8^{a}	4.2^{a}	5.9^{b}	7.7^{a}	40^{a}	38^{a}
SE±	4.8	1.99	0.44	0.22	0.268	0.465	3.1	3.6	1.67	1.11
C.V (%)	8.7	9.5	8.6	14.1	16.6	22.7	9.8	10.6	12.9	10.3
Sig.	*	*	**	**	**	**	*	*	*	*

Means within columns followed by the same letter(s) are not significantly

different at P<0.05 level according to Duncan's Multiple Range Test.
* and ** indicate significance at P≤0.05, and 0.01, respectively.

Table3.Effects of Diammnuim phosphate (DAP) and Chicken manure (CM) on soil bulk density (g cm-3),soil total porosity (%) and soil moisture percentage (%)

Parameters	(Soil Bulk density (g cm-^{3}		(%) Soil Moisture content		(%) Soil Total porosity	
Treatments	1st Season	2nd Season	1nd Season	2 nd Season	1st Season	2 nd Season
Control	1.76a	1.81a	9.3c	9.6c	37.0b	39.0b
DAP	1.53b	1.39b	15.3b	17.7b	48.0a	47.6a
CM	1.43c	1.40b	15.6b	17.3b	49.7a	47.7a
DAP+CM	1.41c	1.38b	16.3a	19.6a	50.0a	50.6a
SE±	1.40	1.44	0.535	0.569	0.659	0.732
C.V (%)	3.99	2.8	9.1	11.2	8.5	7.1
Sig.	***	***	**	**	***	***

Means within columns followed by the same letter(s) are not significantly different at P<0.05 level according to Duncan's Multiple Range Test.
* and ** indicate significance at P≤0.05, and 0.01, respectively.

Conclusion:

According to the above results it can be concluded that chicken manure (4 ton ha $^{-1}$) in addition to diammonuim phosphate (100 Kg ha^{-1}) improve physical properties of infertile soil of Northern State of Sudan and enhanced wheat (Triticum aestivum L.) growth and yield.

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Evaluation of Groundnut(*Arachis hypogaea – Hydysarae*) Losses under Mobile and Stationary Threshing Methods

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Abstract

Mobile and stationary threshing are the two methods used in harvesting groundnut (*Arachis hypogaea – Hydysarae*) crop. Different evaluation parameters were studed for selection the suitable threshing method, their effects on percent losses were pointed out. Threshing losses were affected by the interval from digging to threshing date. Delaying groundnut threshing beyond the recommended date (2 to 6 days after digging date) resulted in increased losses. Mobile threshing resulted in the least percent of losses (11.3%), when compared to stationary threshing.

Keywords: Groundnut, Threshing, Mobile, Stationary, Losses.

مستخلص

الدراس المتحرك والثابت هما طريقتين تستخدمان فى حصاد الفول السودانى (*Arachis hypogaea–Hydysarae*) عدة عوامل تم دراستها لتقييم ولاختيار الطريقة المناسبة للدارس وتاثيرهما على نسبة الفاقد فقد تم تناولها. فاقد الدراس يتاثر بالفترة من القلع الى تاريخ الدراس والتاخير فى الدراس بعد التاريخ الموصى به (6-2)ايام بعد تاريخ القلع) تكون نتائجه زيادة فى الفاقد.

الدراس المتحرك كانت نتائجه قد حققت اقل نسبة فاقد (11.3%) عندما قورن بالدراس الثابت التقليدى.

Introduction

Machines have been developed to harvest most agricultural crops. Agricultural engineers and equipments specialists, employed by machinery manufacture and research centers work continuously to develop new and improved machines. They developed the digger shaker inverter which digs the groundnuts, shakes and inverts it, also a groundnut combine for the threshing, separation, cleaning and handling. The groundnut plant (*Arachis hypogaea – Hydysarae*), It's a weak perennial herb, grown in many tropical and subtropical countries. In regions with longer wet seasons, runner or spreading bunch forms will give the best yield, whilst upright bunches do best in areas of shorter season [1]. The seed of groundnut contain up to 50%of non-drying oil and 35% protein and used in wide range of food industries. Rapid progress has been made since 1950 towards complete mechanization of groundnut harvesting utilizing the windrow combine method in preference to had stacking and stationary threshing,[2]. [3], compared different groundnut harvesting systems. He found that manual threshing required about 315 man-hr/fed which is about five times stationary threshing requirement (61.3 man-hr/fed.), and about nine times the mobile threshing requirement (35-man-hr/fed).,hence stationary threshing twice the requirement of mobile threshing. Results showed that header, tail, and total losses increased significantly (5% level) with decrease of pod moisture content. Also results showed that threshing after two days is better than threshing after five days from digging.[4]. [5]reportedthatthegroundnutcombineharvestersareusedforpicking

the crop directly from windrows. He stated that their use reduced the number of men per operation and total number of man-hours per acre. The main problem which is limiting the use of machines in harvesting lies in the losses of large amounts of the crop caused by mechanical harvesting, such losses results from many factors such as degree of soil moisture at digging time and time of harvesting. The other problem limiting the use of machines is the loss of chaffs when using mobile combine harvester, so there is a need to examine the effect of threshing losses due to mobile and stationary operations. In Rahad Scheme the farmers perform groundnut threshing at different dates from digging time anoptimum date for threshing is not yet know. This study is devoted to assess the groundnut losses as affected by the different threshing methods.

Materials and Methods

This study was conducted at the Rahad Agricultural Corporation (Algaria 27), under tenant farmers conditions. The Rahad Scheme lies east of the Blue Nile on the eastern bank of the Rahad River. The soil of the Rahad Scheme has high clay content (35-40)% montmorillonite), the climate is tropical semi-arid and is characterized by a short raining season [6].

The total area used for the experiment was six feddans divided into small sections of three feddans in each farm. The area was made of 24 plots, hafe of this area treated with mobile and the remain area with stationary threshing method, and each method achieved 2,4,6 and 8 days from last irrigation for the crop. They were divided into three groups of 8 farmers.

Experimental Design

The statistical analysis used in this experiment is Complete Randomized Design (CRD). The mean was obtained with regard to moisture content and its effect in different threshing systems. To obtain differences in means Least Significant Differences (LSD) test technique was used.

Threshing losses

Lilliston 1580 groundnut combine trailed by the Johon Deere 2450 tractor, adjusted and then run to thresh the crop at 2, 4, 6, and 8 days from digging, respectively. Groundnut combine with 12 km/h speed threshed 1/12 of a feddan at each threshing day mobile, and also the same area stationary at each plot and treatment. Threshing losses estimated by calculated the following items: a) header losses: these are the pods which are left on the surface of the ground after the combine header passed. b) Tail losses: these are pods lost with the hay thrown at the back of the combine. c) Total threshing losses: is the sum of the header and tail losses. For the mobile threshing the total losses is calculated by collecting the pods lying onto the packing sacks to represent the tail losses plus that lying under packing sacks which represents the header losses. This was done for each plot separately to form the experiment data. The stationary threshing case is easier and this is obtained by collecting pods which shattered at the combine manual feeding to represent the header loss and at the rear of the combine to represent in turn the tail loss.

Results and Discussion

It was found that the amount of losses due to threshing depends on the digging date. Different threshing methods (mobile and stationary), have shown to have highly significant effect on crop losses as shown on data of tables 1,2,3,4,5, and 6. It indicates that threshing g losses percentage increased for every day passing after digging date, so the optimum date range corresponding to minimum groundnut threshing losses lies between 2 to 6 days after digging date.

Mobile threshing experiment gave losses that ranged from 2.3 to 6.2% with 3.8 mean, for the first threshing day (2 days after digging). At the

4th day the losses ranged from 5.7 to 12.4 with a mean equal to 7.3, while the losses on the 6th day ranged from 11.3 to 18.0 with a mean equal to 14.5%. The mobile threshing losses for the 8th day from digging was found to range between 18.3 and 22.1% with 19.7 mean, these results are given in tables 1,2 and 3. Results of the experiment showed that there highly significant differences in threshing losses as time pass after digging date. When the pods are over exposed the windrow permits moisture to evaporate rapidly and that decreases the pods weight. This makes the pods lighter, although can be thrown outside the combine together with the vines, that would also add up to the threshing losses.

Table (1): Effect of mobile threshing and different threshing dates on threshing losses

Threshing Date / Threshing Method	2	4	6	8
Mobile	15.6	17.5	19.4	27.8
	15.7	23.7	26.4	26.4
	17.2	10.6	12.4	14.2
Mean	16.2	17.2	19.3	22.8

Table(2): CRD analysis of the data of table (1).

Source of Variance	Degree of Freedom	F Calculated	F Tabulated 0.01	F Tabulated 0.05	Degree of Significance
Dy	3	18.02	4.07	7.59	**
Error	8				

Table (3): LSD test of the CRD analysis of table (2)

Comparison	Dy8 – Dy2	Dy8 – Dy4	Dy8 – Dy6	Dy6 – Dy2	Dy6 – Dy4	Dy4 – Dy2
Comparison Value	**15.89	**10.65	*5.26	**10.63	*5.06	*5.24

Dy = Different reading days (2-8) from digging date

Highly significant = **

LSD 0.05 = 4.3

LSD 0.01 = 6.7

On the other hand, results of the stationary threshing experiment showed significant differences in losses depending on the threshing date after digging. The losses values obtained when threshing was done after digging, ranged from 19.3 to 23.2 with a mean value equal to 25.9% as shown in tables 4, 5, and 6. The time factor effect on threshing losses for the mobile or stationary threshing .is presented on figure 1

Table (4): Effect of stationary threshing and different threshing date on the threshing losses%

Threshing Date / Threshing Method	2	4	6	8
S Stationary	16.13	10.42	18.15	23.18
	7.29	12.14	14.29	19.31
	11.28	16.37	19.55	27.73
Mean	8.2	12.9	17.3	23.4

Table (5): CRD analysis of the data of table (4).

Source of Variance	Degree of Freedom	F Calculated	F Tabulated 0.01	0.05	Degree of Significance
S	3	11.95	4.07	7.59	**
Error	8				

Table (6): LSD test of the CRD analysis of table (5)

Comparison	Dy8 – Dy2	Dy8 – Dy4	Dy8 – Dy6	Dy6 – Dy2	Dy6 – Dy4	Dy4 – Dy2
Comparison Value	**15.2	**10.4	*6.1	**9.1	*4.1	4.8^{NS}

Dy = Different reading days (2-8) from digging date

Highly significant = **

Significant = *

NS = Not Significant

LSD 0.05 = 4.8

LSD 0.01 = 7.5

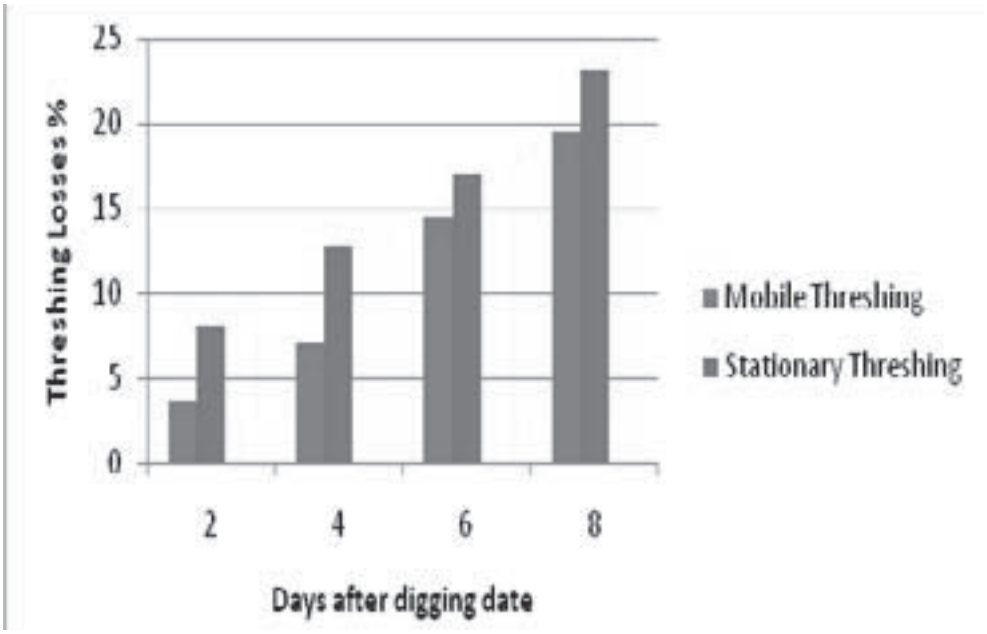

Figure 1: Effect of threshing method and time from digging date on groundnut losses

It was found that differences were more pronounced in the mobile threshing when compared to the stationary threshing. The reason for this could be that many pods were shattered when windrow regime was used; hence the mobile threshing permits the combine to work of high efficiency than stationary threshing. On the other hand, if the combine is threshing on move it will attain its proper capacity, rather than being stationary and fed by labors in which case over-feeding might take place and lead to the miss-use of the combine and therefore, resulting in more threshing losses.

LSD test results for the CRD data of mobile threshing losses on different threshing days from digging date are shown on table 15. It was observed that the threshing losses mean for 8th -2nd , 8th -4th

, and 6th – 2nd , threshing days are different with high significance, while the threshing losses mean for 8th -6th , 6th -2nd , and 4th -2nd , threshing days are significantly different. The results of the experiments of head and tail losses were presented on table 7.

Table (7): Tail and header losses on different reading days

Treatment		Header Losses		Tail Losses		Total Losses
Treat-ment Method	Days from Digging	(WT (kg	%	(WT (kg	%	Total (WT (kg
Mobile	2	0.82	2.78	0.27	1.04	1.09
	4	1.91	6.88	0.62	2.18	2.53
	6	3.02	10.81	1.02	3.64	4.04
	8	3.89	14.79	1.30	4.93	5.19
Station-ary	2	0.62	2.05	1.86	6.18	2.48
	4	0.98	3.45	2.71	9.53	3.69
	6	1.19	4.38	3.52	12.95	4.71
	8	1.45	5.79	4.41	17.62	5.86

Conclusion:

From the results of experiment can conclude those 2 to 6 days after digging is enough for the groundnut to be left under the sun rays to dry, and then be ready for threshing cleaner groundnut was obtained. Mobile threshing has proved to result in the least amount of losses, despite fact that chaff may be lost, it give better results and proved to save time

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Genetic Coefficient of Variability, Heritability and Genetic Advance in Five Groundnut (Arachis hypogaea L .) Varieties Under Two Sowing Methods under Northern Sudan Conditions

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Abstract:

Field experiments were carried out over two seasons of the years 2016 and 2017 to evaluate five groundnut (*Arachis hypogaea L.*) varieties (Medani, Sodari Ahmadi, Karaz and Tozi) at Dongola-Sudan. Factorial Randomized Complete Block Design (RCBD) with three replications was used to layout the experiments. The treatments were five varieties and two sowing methods (flat and ridges), where Phenotypic variability was determined. Then, phenotypic (δ^2ph) genotypic (δ^2g) and environmental (δ^2e) variances, genotypic coefficient of variation (GCV) , heritability (h^2) and genetic advance (GA), were estimated for 14 characters including seed yield /ha. The highest GCV was given by pod yield kg/ha in the two seasons, whereas the lowest one was exhibited by days to maturity in the first season and plant height in the second season. Characters that gave higher ≥ 50 to moderate ≥35 estimates of heritability include seed yield kg/ha, days to 50% flowering and pod yield kg/ha in both seasons; plant height, days to maturity, 100 seed weight and seed yield/plant in the first season. However, none of the characters gave higher to moderate estimate of heritability in the second season only. The highest GAM was exhibited by pod yield /ha, seed yield /plant and seed yield /ha while the lowest by days to maturity. High heritability was associated with high genetic advance (GAM) for seed yield kg/ha and with low genetic advance for plant height, days to 50%flowering, main stem diameter, 100 seed weight, pod yield/plant and seed yield/plant. Moderate heritability was associated with high genetic advance for pod yield kg/ha. The genetic advance followed the same pattern as that of the GCV. The highest genetic advance was shown by pod yield kg/ha (921.677) in the first season and (113.453) in the second season .both in flat sowing

Key words: groundnut- heritability- GCV- genetic advance

مستخلص:

أجريت تجربة حقلية لموسمين متتاليين خلال السنوات 2016 و 2017 وذلك لتقييم خمسة اصناف من الفول السوداني (Arachis hypogaea L.) وهي: مدني، سودري، احمدي، كرز وتوزي في منطقة دنقلا –الولاية الشمالية– السودان. تم تصميم تجربة عاملية باستخدام تصميم القطاعات العشوائية الكاملة بثلاث مكررات لتنفيذ التجربة حقليا. المعاملات في هذه التجربة تمثلت في الخمسة أصناف من الفول السوداني بالإضافة لطريقتين للزراعة هما مسطح وسرابات، حيث وضعت الأصناف في القطع الرئيسية وطريقتي الزراعة في القطع الجزئية. تم تقدير التباين المظهري والتباين الوراثي والتباين البيئي ومعامل الاختلاف الوراثي ودرجة التوريث والتقدم الوراثي لأربعة عشرة صفه شملت الإنتاجية من البذور للهكتار. سجلت أعلي قيمة لمعامل الاختلاف الوراثي لصفة إنتاجية القرون /الهكتار بينما كانت الأقل لعدد الأيام للنضج في الموسم الأول وارتفاع النبات في الموسم الثاني. سجلت أعلي قيمة لدرجة التوريث لصفات انتاجية البذور /الهكتار وعدد الأيام للإزهار بنسبة 50% وإنتاجية القرون/للهكتار في الموسمين ولصفات ارتفاع النبات وعدد الأيام للنضج ووزن الـ 100 حبة وإنتاجية البذور/ النبات في الموسم الأول. سجل أكبر تقدم وراثي لصفة إنتاجية القرون /للهكتار بينما كان الأقل لصفة عدد الأيام للنضج. شملت الصفات ذات درجة التوريث العالية أو المتوسطة (≥ 50%و≥ 35%) كل من الإنتاجية من البذور/ الهكتار وعدد الأيام للإزهار بنسبة 50% وانتاجية القرون /الهكتار في الموسمين. بينما شملت الصفات ذات درجة التوريث العالية أو المتوسطة في الموسم الأول صفات طول النبات وعدد الأيام اللازمة للنضج ووزن الـ 100 حبه وانتاجية البذور للنبات ولم تكن هنالك أي صفة ذات درجة توريث عالية أو متوسطة في الموسم الثاني. سجلت أعلي قيمة للتقدم الوراثي لصفات إنتاجية القرون /الهكتار وإنتاجية البذور /النبات وإنتاجية البذور /الهكتار بينما كان الأقل لعدد الأيام للنضج. ارتبطت قيمة درجة التوريث العالية مع قيمة التقدم الوراثي العالية لصفة إنتاجية البذور للهكتار ومع قيمة متدنية للتقدم الوراثي مع صفات ارتفاع النبات وعدد الأيام للإزهار 50% وقطر الساق الرئيسي ووزن الـ 100 حبه وإنتاجية القرون للنبات وإنتاجية البذور للنبات. كما ارتبطت قيمة درجة التوريث المتدنية مع قيمة التقدم الوراثي العالية مع صفة إنتاجية القرون/للهكتار. اتبع التقدم الوراثي نفس النمط لمعامل الاختلاف الوراثي(GCV) بينما لم توجد علاقة محددة بين درجة التوريث من جهة وبين أي من التقدم الوراثي أو معامل الاختلاف الوراثي

Introduction

The cultivated groundnut (*Arachis hypogea L.*) was originated in South America (Bolivia and adjoining countries) and is now grown .throughout the tropical and warm temperate regions of the world Groundnut seeds (kernels) contain 40-50% fat, 20-50 % protein and 10-20 % carbohydrate. Groundnut seeds are nutritional source of vitamin E, niacin, falcon, calcium, phosphorus, magnesium, zinc, iron, riboflavin, thiamine and potassium. Groundnut kernels are consumed directly as raw, roasted or boiled. Oil extracted from the kernel is used as culinary oil. It is also used as animal feed (oil pressings, seeds, green material and straw) and industrial raw material (oil cakes and fertilizer). These multiple uses of groundnut plant makes it an excellent cash crop for domestic markets as well as for foreign trade in several developing and developed countries [1].

In the Sudan Groundnut plays an important role in the diets of rural populations, particularly children, because of its high nutritive value. protein content was 21-30% fat 41-52% and carbohydrate 11-27%. The byproduct of oil extraction is an important ingredient in livestock feed. Groundnut haulms are nutritious and widely used for feeding livestock. Groundnut *(A. hypogaea L.*; family, Fabaceae) is an important crop among oilseeds. It is a self-pollinated, with chromosome number (2n=40) and was grown in tropical and sub-tropical regions of the world.

It is grown on 26.4 million hectares worldwide with a total production of 37.1 million metric tons and an average productivity of 1.4 metric tons/ha [2] with a worldwide average yield of 1348 kg/ha. The production of groundnut is concentrated in Asia and Africa (56% and 40% of the global area and 68% and 25% of the global production, respectively). India, China and the United States have been the leading producers for over 25 years and grow about 70% of the world crop. Nigeria has biggest area under groundnut cultivation and also the biggest producer in Africa. The Sudan, cultivated about 1900 hectares of groundnut which produced 1200 metric ton with an average yield of 632 kg/ha [3]. In the Sudan, groundnut is important oil and cash export crop. Area under cultivation the crop is about 0.8 million hectares with an estimated total production of 0.4 million tons [4]. The crop is grown under irrigation in the central clay plains and in the rain fed areas in the sandy soils of western Sudan. About 80% of the area and two third of the national production come from the traditional rain fed sector of western Sudan. In North Kordofan, groundnut comes after sorghum in area under cultivation. Barbeaton, sodiri and Gubiesh, are widely grown cultivar characterized by early maturity, The main problem of the groundnut production in the Sudan is finding of the

suitable variety for the different parts of the country; therefore, the objective of this study is to assess the performance of five released cultivars under Modern Surface irrigation system at Dongola Research Station Demonstration farm.

Literatur Review

Heritability, genetic coefficient of variation and genetic advance: Broad-sense heritability estimate helps in identifying the appropriate character for selection [5]. This is because, variability observed in some characters is caused primarily by differences in genes carried by different individuals, however, variability in some other character is due primarily to differences in the environment to which individuals have been exposed or genotype x environment interaction. The heritability estimate thereby, specifies and quantifies the relative importance of heritable variation and environmental variation in determining the expression of a character [5,6], in study of a number of characters in soybean (Glycine max) indicated that estimate of heritability along with genetic coefficient of variation is more useful in predicting the resulting effect of selection than heritability values alone because of the effect of sample size, environment, the character and population on heritability estimates. Moreover, heritability indicates the confidence on which selection of genotypes can be based rather than phenotypic performance. It does not provide an indication of the amount of genetic progress from selection. Since genetic progress increases with the increase in genetic variance, the utility of heritability estimate increased when it used in conjunction with selection differential. It is evident that the genetic coefficient of variation x selection differential provides information concerning the maximum effect of selection, while heritability indicates how closely this maximum can be reached [5]. In ground, [7,8] reported high heritability along with high genetic ad-.vance for pod yield, kernel yield, 100 kernel weight and days to maturity working in ground nut genotypic coefficient of variation (GCV), phenotypic coefficient of variation (PCV), heritability h^2 and genetic advance as percentage of mean (GAM) were estimated for yield, yield attributes among 28 F_2 ground nut population [9,7]. Phenotypic coefficient of variation was of higher magnitude than the genotypic coefficient of variation for all characters indicating the influence of environment in expression of the traits. [10,11] and [9] reported high GCV for number of secondary branches per plant (34.42%), percentage of leaves affected by foliar diseases (49.98%) and number of immature pods per plant (20.80%). Heritability was low for number of secondary branches per plant (7.47%) with moderate GAM (19.38%). For the other two traits, both heritability and GAM were high. However, [10,12]

[11,13] detected moderate GCV for number of primary branches per plant. [14,15], [16,17], [18,19], [20,21] reported high estimates of heritability for days to 50% flowering (82.63%), plant height (80.00%), seed yield per plant (72.73%), kernel yield (72.63%), pod yield per plant (70.56%), pod yield kg/ha (67.03%), moderate estimates of heritability for kernel uniformity (57.46%), days to maturity (54.89%), number of primary branches (51.34%) and field emergence (33.59%) and low estimate of heritability for shelling percentage (27.44%). [22] reported that high PCV and GCV were exhibited by biological yield per plant and biological yield per hectare, indicating greater variability and scope for improvement of high yielding varieties. Similarly, Zaman *et al*. [23] and John *et al*. [22] reported high PCV and moderate GCV for pod yield per plant, pod yield per hectare, kernel yield per plant, kernel yield per hectare indicating possibility for selection of good varieties with regards to these traits. However, [24] and [25] reported that days to 50% flowering, days to maturity, shelling percentage and oil content exhibited low PCV and GCV indicating the presence of low variability among the tested genotypes. [22] and [8], Indicated high heritability estimates for kernel yield per plant, kernel yield per hectare and oil yield per hectare indicating little influence of environment on the inheritance of these characters. [22] and [25] reported high heritability coupled with high genetic advance as per cent of mean was recorded in kernel yield per plant, kernel yield per hectare, 100 kernel weight and oil yield per hectare indicating the prevalence of additive gene action in governing the inheritance of these characters and offers great scope for improvement through simple selection procedures. [22] indicated moderate heritability coupled with high genetic advance as percent of mean for biological yield per plant, pod yield per plant, biological yield per hectare and pod yield per hectare. On the other hand, moderate heritability accompanied with low genetic advance as percent of mean was recorded in days to 50% flowering, days to maturity, shelling percentage [9] and [23].

Materials And Methods

The Field experiments were conducted at the Demonstration Farm, Dongola Research Station- northern state of the Sudan. The northern state of the Sudan occupies the distant northern part of the Sudan and lies between latitudes16 – 22N and longitudes 20 – 32 E. The experiment was conducted during seasons .of 2016 and 2017

Five released cultivars of groundnut (*A. hypogea L.*) were grown under conditions of the northern state of the Sudan under two sowing methods in factorial randomized complete block designs (RCBD) with three replications. The five cultivars (Medani, Sodari, Ahmadi, Karaz and Tozi) being assigned

to the main plot whereas the two sowing methods (flat and ridges) to the and ridge-to-ridge (or row to row) spacing were subplots. The hole-to-hole 30 cm and 60 cm respectively with plot size 3 x 3 m. In both seasons, sowing date was 24 th July. The irrigation water was applied at an interval of 8 – 10 days in both seasons. In both seasons, weeding was carried out by hand and no fertilizer was applied. For data collection, five randomly selected plant per plot were used, in both seasons to study the following characters: Plant height (cm), days to 50% flowering, days to maturity, Main stem diameter (cm), biomass(g), number of reproductive branches/ plant, number of pods/ plant, number of pods/ branch, number of seeds/pod, 100-seed weight, .pod yield/plant, seed yield/plant, pod yield(kg)/ha and seed yield(kg)/ha Theprocedure described by [26] was used to estimate the individual and combined analysis of variance. Individual analysis of variance was carried out each season separately; then combined analysis of variance was done for those characters in which the mean squares of error (b) were homogenous. Then genotypic, pheno-:typic and environmental variances were calculated according to [26] as follows

Table 1. The form of analysis of variance, based on a randomized complete block design (RCBD) used in estimation of genotypic (δ^2g), environmental(δ^2e), and phenotypic(δ^2ph) variances.

Source of variation	d.F	MS	E.M.S
Replication (r)	r - 1 = 2	M3	
Genotypes (g)	G – 1 = 4	M2	$\delta^2e + \delta^2g$
Error	(r-1)(g-1) = 8	M1	δ^2e
-	- Total		rg-1 = 14

:Where

.r = Number of replications

.g = Number of genotypes

M1, M2 and M3 = Mean squares for error, genotype and replica-.tions, respectively

.[After Gomez and Gomez [26

- :phenotypic and genotypic variances

Phenotypic (δ^2_{ph}) and genotypic (δ^2_g) variances based on RCBD design :were estimated using individual analysis of variance (table 4), as follows

$$\delta^2_g = M_2 - M_1/r$$

$$\delta^2_{ph} = \delta^2_g + \delta^2_e$$

:where

$\delta^2_e = M_1$

- :Genetic coefficient of variation

Genetic coefficient of variation (GCV) was computed following :by[27] as

$GCV = (\delta^2_g / G) \chi 100$

Heritability: -

Heritability (h^2) in broad sense was estimated for each character :using the procedure of [5] as

$h^2 = \delta^2_g / \delta^2_{ph}$

Genetic advance under selection: -

Expected genetic advance under selection (GA) was estimated following [6]. Then, the estimated GA was expressed as percentage of the overall mean :of the character

$GA = K\ \delta^2 g/\delta^2 p$

$GAM = (GA\ \chi\ 100)/ G$

:Where

.K = the selection differential, and it equals 2.06 for 5% selection intensity

Results And Discution

A wealth of phenotypic variability is pre-requisite for any successful breeding program. This is due to the fact that; selection does not create variability but only acts on that already existing. This variation can be quantified by genotypic, environmental and the genotype x environment interaction components. The relative magnitude of these components determines the genetic property of the population. This is accomplished by .estimation of the heritability versus environmental effect on the genotype

Phenotypic, genotypic and environmental variances

The result of the environmental variances revealed great variance for days to 50% flowering and pod yield kg/ha in estimates of environmental variances between the two sowing methods in both seasons (table 2). Similar results were obtained by [28]. On the other hand, number of pods/plant, 100 seed weight, pod yield/plant and seed yield/plant exhibited great variations in estimates of environmental variances between the seasons in both sowing methods (table 2). Similar fundings were reached by [29]. The estimated values of genotypic variances in the first season were greater than in the second season in both sowing methods in most of the characters with exception of pod yield kg/ha & seed yield kg/ha (table 2). This result can be attributed to

environmental effects. Similarly, the estimated values of genotypic variances in the flat sowing method were greater than in the ridge sowing method in .most of the characters with exception of pod yield kg/ha & seed yield kg/ha Pod yield kg/ha and biomass/plant showed great variations in the estimates of genotypic variances between the two sowing methods in both seasons (table 6). Similar results were reached by [30,31] and [32]. On the other hand, plant height, number of branches/plant, 100 seed weight, seed yield/plant exhibited greater variation in estimates of genotypic variances between the two seasons in both sowing methods (table 6). Similar result war obtained by [33]. Furthermore, number of pods per plant and per branch in both seasons in ridge sowing and the first season in flat sowing, days to maturity and pod yield / plant in the second season, main stem diameter in flat in the first season and days to maturity, main stem diameter, seed yield / plant and pod yield / ha had higher environmental variances than phenotypic ones. Thus, indicating that the genetic variance was negative therefore, estimate of genetic variance was difficult to calculate for these traits. Similar estimate of negative genotypic variance was reported by [34,35]. The estimated values of phenotypic variances in the first season were greater than in the second season in both sowing methods with the exception of seed yield/plant and pod yield kg/ha in each season. The estimated values of phenotypic variances in the ridge sowing methods were greater than in the flat sowing methods with the exaptation . of number of branches/plant

seed yield kg/ha, 100 seed weight and number of branches/plant showed great variations in the estimates of phenotypic variances between the two seasons in both sowing methods (table 2). Similar result was obtained by [36]. Estimates of phenotypic variances followed the same pattern of genotypic variances where days to 50% flowering and to maturity days and main stem diameter gave more or less the same estimate of phenotypic variances. On the other hand, pod yield kg/ha and number of branches/plant exhibited greater varia- .tions in estimates of phenotypic variances between the two sowing methods

Genetic coefficient of variation, broad sense heritability and genetic advance: -

Genetic coefficient of variability determines the degree of the genetic variability expressed by a character in a population. Moreover, amount of genetic variability is a major determinant of the genetic gain from selection. In this study, a wide range of genetic coefficient of variability was detected among the evaluated varieties for the studied characters. GCV estimates for all characters fluctuated over the two seasons and the two sowing methods, with the exception of days to flowering and days to maturity, which gave more or less similar estimates of GCV over both seasons and both sowing methods. In both

seasons and both sowing methods, the highest values of GCV were exhibited by seed yield/plant, pod yield/ha and seed yield/ha while the lowest GCV was exhibited by days to maturity both in the first season (table 3). [37], in hyacinth bean and [35], in guar reported similar result for days to maturity. The highest genetic advance (GA) was given by pod yield/ha and seed yield/ha. On the other hand, the lowest values of genetic advance were shown by biomass/plant in the first season and main stem diameter in the second season both in flat sowing (table 3). Consequently, the highest genetic advance (GA%) over both seasons and both sowing methods were obtained for seed yield/plant, pod yield/ha and seed yield/ha while the lowest GA% was exhibited by days to maturity both in the first season. This is because the genetic advance from selection in any character depends mainly on the genetic variability [6]. The low values of GA for days to maturity and other characters thereby could be attributed to low GCV expressed by a character. Similar re-. sults were obtained by [38,35] in guar ,[34] in faba bean and [37] in lablab bean Heritability, an important measure of the inheritance of a trait, specifies the portion of the total variance that is attributable to the average effect of genes. Thus, its main role is in predicting the reliability of the phenotype as a guide to the genotypic performance. Heritability of a character and its phenotypic performance, coupled with selection intensity and the amount of variabil-.ity present in the population, influence the amount of gain from selection Regarding heritability estimates, a wide fluctuation in the over season and sowing methods values were detected for almost all characters under study with the exception of days to flowering and 100-seed weight in flat sowing. This variation in magnitude of heritability could be attributed to influence of environmental factors. [39] attributed reduction in heritability estimate to the effect of variable conditions. Similar results in fluctuations of heritability estimates with change of environment in groundnut were detected by [7,8]. In this study, characters which gave higher ≥ 50 to moderate ≥35 estimates of heritability in the two seasons and over the two or one sowing method include seed yield /ha, days to 50%flowering and pod yield / ha. In additions, plant height, days to maturity, 100- seed weight and seed yield /plant gave high to moderate estimate of heritability only in the first season and over the two or one sowing method (table 7). [20] .and [21] found high estimates of heritability for days to 50%flowering In this study, the genetic advance (GA) ranged from 0.102 for stem diameter to 921.677 for pod yield kg/ha both in flat sowing. However, the genetic advance as per of mean (GAM) ranged from 0.49 for days to maturity (in ridge sowing) to 359.879 for pod yield kg/ha (in flat sowing). Charac-

ters, which gave high estimate of GAM, include biomass/plant in the first season in flat sowing, pod yield/plant in ridge sowing, in the two seasons and seed yield/plant in flat sowing in the first season and in ridge sowing in the two seasons), pod yield kg/ha, in flat sowing in the two seasons and in ridge sowing in the first season) and seed yield kg/ha in flat sowing (table 3). Very low estimates of GAM were recorded for plant height (0.789% in the second season in flat sowing and days to maturity (0.491% in the first season in ridge sowing). Other character gave low estimate, ranging from 2.325% for main stem diameter in flat sowing in the first season to 8.637% for number of pods/branch. The character 100 seed weight exhibited moderate estimate of GAM (14.585%) in flat sowing in the first season. In this study, high heritability was associated with high genetic advance (GAM) for seed yield kg/ha (table 7). Similar funding was obtained by [22,25]. Although in this study the results obtained from application of 50% selection pressure indicated that the estimate of genetic advance was closely associated with magnitude of GCV, there was no definite pattern of association between heritability estimate and either GCV or genetic advance. Therefore, heritability estimate would be meaningful if it is accompanied by GCV in predicting the genetic advance from selection. In this regards, the highest genetic advance was obtained for characters that had the highest GCV, namely seed yield/plant, pod yield/ha and seed yield/ha. High heritability was associated with low genetic advance for plant height, days to 50%flowering, main stem diameter, 100 seed weight, pod yield/plant and seed yield/plant in both sowing methods. Moderate heritability with high genetic advance for pod yield kg/ha in both sowing methods. Similar findings were reached by [22]. Thus, high heritability value was not always associated with high genetic advance. This is because heritability measures the degree of closeness between the genotypic and the phenotypic variances, regardless of being high or low. Hence, it provides no indication of the actual magnitude of genotypic variation. On the other hand, the genetic gain depends on the amount of genotypic variability. Moreover, heritability in broad sense includes, in addition to additive genetic variance, non-additive genetic variance due to dominance and epistasis [40]. Therefore, heritability estimate would be meaningful if accompanied by GCV in predicting the expected genetic advance. [5] concluded that estimate of heritability along with GCV are useful in predicting the effect of selection than h^2 values alone, because of the effect of sample size, environment, the character and the population on heritability estimates.

The nature of association between heritability and genetic advance was explained by [41]. He reported that the association of low heritability with low

genetic advance is an indication of non-additive gene effect and consequently low genetic gain is expected from selection. On the other hand, an association of high heritability with high genetic advance is indicative of additive gene effects, and consequently a high genetic gain from selection would be anticipated. Thus, according to [41], the coupling of high estimate of heritability and comparatively high estimate of genetic advance for pod yield kg/ha could be attributed to additive gene action and hence selection for this characters would be effective. On the other hand, the association of low heritability with low genetic advance for plant height, days to 50%flowering, main stem diameter, 100 seed weight, pod yield/plant and seed yield/plant in both sowing methods would indicative of low additive gene effect and hence selection will not be effective for these characters.

Table (2) Genotypic variance ($\delta^2 g$), phenotypic variance ($\delta^2 ph$) and environmental variance ($\delta^2 e$) in five ground nut (A. hypogaea L) varieties evaluated at four environments (two seasons (2016 and 2017) and two sowing methods (flat and ridge).

Character	δ^2 e				δ^2 g			
	Flat		Ridge		Flat		ridge	
	2016	2017	2016	2017	2016	2017	2016	2017
(Plant height(cm	0.833	2.061	5.033	1.044	1.117	0.076	-	0.399
Days to50% flowering	0.788	0.300	0.150	0.067	0.722	0.7	1.42	0.73
Days to maturity	0.600	1.433	0.6	1.600	0.333	-	0.33	-
Main stem diameter	0.579	0.355	0.433	0.357	-	0.031	0.117	-
Number of branch/plant	4.733	1.150	1.733	1.233	1.733	0.083	0.83	-
Number of pods/ plant	69.633	33.317	94.867	62.783	-	3.317	-	-
Number of pods/ branch	5.233	1.567	1.817	3.117	-	0.233	-	-
Number of seeds/pod	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
seed weight 100	73.767	37.331	110.417	25.001	40.83	3.513	16.92	3.752
Biomass/plant	0.000	0.000	0.001	0.000	0.001	0.000	0.000	0.000
pod yield/plant	24.650	426.667	51.859	519.583	6.417	-	63.12	-
Seed yield/plant	31.599	148.306	30.209	255.069	25.036	4.856	19.11	-
pod Yield Kg/ha	2790.811	2761.293	6055.244	7652.542	3567.652	4783.869	4712.25	-
seed yield Kg/ha	889.907	1441.056	2816.805	517.860	1281.122	1427.327	2306.73	931.75

Continue table (2):

Character	δ^2 p			
	Flat		Ridge	
	2016	2017	2016	2017
(Plant height(cm	2	2.137	-	1.443
Days to50% flowering	1.455	1	1.57	0.797
Days to maturity	0.933	-	0.93	-
Main stem diameter	-	0.386	0.55	-
Number of branch/ plant	6.466	1.233	2.563	-
Number of pods/plant	-	36.63	-	-
Number of pods/ branch	-	1.8	-	-
Number of seeds/pod	0.000	0.000	0.000	0.000
seed weight 100	114.597	40.844	127.337	28.753
Biomass/plant	0.001	0.000	0.001	0.000
pod yield/plant	31.067	-	114.71	-
Seed yield/plant	56.135	153.162	49.319	-
pod Yield Kg/ha	6358.463	7545.162	10767.49	-
seed yield Kg/ha	2171.029	2868.383	2819.11	1449.61

Table (3) Genotypic coefficient of variation (GCV) heritability (h2) in 5 groundnut (A. hypogaea L) varieties evaluated at 4 environments (two seasons (2016 and 2017) and two sowing methods (flat and ridge).

	GCV				**H**			
	Flat		Ridge		Flat		Ridge	
Character	2016	2017	2016	2017	2016	2017	2016	2017
(Plant height(cm	8.011	0.560	-	2.973	55.85	3.556	-	27.650
Days to50% flowering	1.508	1.446	2.954	1.516	49.621	70	90.445	91.593
Days to maturity	0.232	-	0.230	-	35.691	2.138	35.483	-
Main stem diameter	-	0.706	2.777	-	-	8.031	21.272	-
Number of branch/plant	19.693	1.804	9.291	-	26.801	6.731	32.383	8.826
Number of pods/ plant	-	15.695	-	-	-	9.055	-	-
Number of pods/ branch	-	5.637	-	-	-	12.944	-	-
Number of seeds/pod	0	0	0	0	0	0	0	0
seed weight 100	75.797	7.898	34.530	7.167	35.629	8.601	13.287	13.049
Biomass/plant	0.917	0	0	0	100	0	0	0
pod yield/plant	22.076	4.464	195.702	-	20.655	-	55.025	-
Seed yield/plant	164.710	17.545	112.062	-	44.599	3.170	38.747	-
pod Yield Kg/ha	1393.031	1665.965	1909.030	-	56.108	63.403	43.763	-
seed yield Kg/ha	854.423	1012.123	1520.987	562.338	59.009	49.760	81.824	64.275

Continue table (3):

Character	GA				%GA			
	Flat		Ridge		Flat		Ridge	
	2016	2017	2016	2017	2016	2017	2016	2017
Plant height((cm	1.627	0.107	-	0.684	11.677	0.789	-	5.096
Days to50% flowering	1.233	1.442	2.336	1.685	2.575	2.979	4.859	3.500
Days to matu-rity	0.710	-	0.705	-	0.494	-	0.491	-
Main stem diameter	-	0.102	0.337	-	-	2.325	7.999	-
Number of branch/plant	1.404	0.154	1.068	-	15.954	3.347	11.955	-
Number of pods/plant	-	1.129	0.871	-	-	5.342	2.240	-
Number of pods/branch	-	0.357	0.726	-	28.191	8.637	11.584	-
Number of seeds/pod	0	0	0	0	0	0	0	0
seed weight 100	7.857	1.132	3.088	1.441	14.585	2.545	6.302	2.752
Biomass/plant	0.066	0	0	0	60.550	0	0	0
pod yield/plant	2.371	-	12.140	16.127	8.157	-	37.639	24.938
Seed yield/plant	6.883	0.809	5.606	12.187	45.282	2.923	32.287	34.546
pod Yield Kg/ha	921.677	113.453	93.549	15.475	359.879	39.509	37.898	4.774
seed yield Kg/ ha	56.640	54.900	89.497	50.413	37.775	38.929	59.011	30.425

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